What shapes climate change beliefs in Africa?

A random forest approach

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Abstract

Although Africa is projected to be 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 second order political boundaries across 33 countries. Second, we employ a novel machine learning methodology within the social sciences (random forest). Finally, we take a holistic approach that incorporates most of the previous predictors identified largely in Western countries to examine whether they hold true in Africa.

The remainder of this article is structured as follows. First, we briefly review the current literature on the factors that shape climate change beliefs. We then explain our data collection and operationalization process, as well as the specification of our random forest models. Finally, we discuss the main findings aggregated across dimensions, to offer clear patterns of what shapes climate change beliefs in Africa.

What shapes climate change beliefs

There is widespread recognition that climate change is real and that its observable consequences can already be appreciated [13]. Nonetheless, anthropologic climate science denial persists among the public—either because of lack sufficient of information, poor understanding of the matter, or because they associate climate science with conspiracy theories (e.g., willful ignorance). For instance, recent survey data from Africa suggests that only 56 % of the continent's population have heard about climate change and about 20% believe that ordinary citizens can do nothing to stop climate change [7]. Why do these disbeliefs persist, or in other words, what shapes individual climate change beliefs? A growing number of interdisciplinary studies suggest four possible answers. First, despite the growing availability of climate change information much of it remains inaccessible for many who do not understand or are not able to reach it. Second, despite having access to climate change information, people's religious beliefs or political ideology can lead to a clash that often results in a biased interpretation of facts. Third, information about climate change is too abstract, leaving people to interpret climate change trough their own personal experience with local climate. Finally, people have a “finite pool of worry”—more urgent concerns than climate change—pushing climate change concerns to the backburner.

Barriers to climate change information

This argument suggests that individuals do not form correct beliefs about climate change because they face barriers to accessing climate information. For instance, not having a cellphone or not having access to the internet are important barriers to discovering current debates, facts and stories about climate change, reducing the amount of information that can improve CCBs [11,12]. Similar studies indicate the importance of social media platforms as forums for climate debates among the public [14]; however, these platforms can also serve as echo chambers where previous beliefs are not contrasted, but continuously reinforced [15]. Another important barrier to information access is education, given that it provides a more detailed understanding of the climate cycle and how humans negatively impact it. Moreover, in-depth case study evidence suggests that even when climate change information is available, a less educated public may lack the tools to understand it, inducing incorrect beliefs [16]. This is further corroborated by large-*N* studies that find a statistical relationship between higher levels of education and more accurate climate change beliefs [10–12,17,18].

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 [19]. This phenomenon, known as motivated reasoning, has been shown to influence individual CCBs, mainly for political and religious motivations [4,10,20]. For instance, Hart and Nisbet [21] 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. Similarly, religious beliefs induce individuals to interpret climate change facts in a way that avoids conflict with their beliefs. For instance, individuals who believe in a deity are more likely to attribute climate change and its repercussions to that deity’s will rather than to human activity [16,22]. Similarly, attending religious services has been linked to more incorrect CCBs [23]. However, these effects may vary across religions [24,25]. Thus, even when people have access to rigorous information and the ability to understand it, politically or religiously motivated reasoning can lead to incorrect beliefs.

Understanding climate change trough personal experiences

A second psychological approach suggests that individuals perceive climate change as a distant phenomenon which is more likely to affect people living in other regions and in the distant future [26]. This psychological distance from climate change often results in a lack of emotional responses to it [27,28]. As a consequence, individuals try to make sense of the changing natural world around them using more available and emotionally salient cues, such as local climate or extreme weather events and their consequences

[26]. This so-called attribute substitution suggests that personal experiences, which are easily accessible and emotionally close to the individual, often replace science-based evidence and climate change facts [4,29]. Previous literature has found that individuals who experience extreme climate-related events such as hurricanes, floods, or temperature anomalies tend to perceive climate change as a greater risk [23,30–35]. Even less extreme events, such as a hotter-than-usual day, can make people more aware of and concerned about climate change [36], and to donate more money to environmental charities [37]. To sum, personally experiencing climate anomalies can enhance climate change beliefs.

Climate change facts take a backseat

A final argument postulates that individuals have more urgent daily concerns (e.g., "bread and butter" issues), which relegate climate science information and its possible consequences to the backburner [11,12,38–40]. In other words, CCBs are deemed less important than immediate day-to-day concerns. This does not suggest that people do not care about climate change and its consequences, but rather, they are seen as distant occurrences that can be dealt with when they disrupt or exacerbate more pressing matters [41].

Demographics

Besides the four previously discussed pathways that account for the climate change information and beliefs linkages, previous research also finds that gender, age, and ethnicity can play a role in shaping CCBs — yet a lack of consensus remains within the literature. When it comes to gender, some studies find that women are less aware of climate change than men but have higher risk perception [16,18,27,42], while others find no statistical relationship between gender and climate change beliefs [10,12,43,44]. Some studies have suggested that differences in the access to climate information could explain this difference [45]. Regarding age, many studies find that young people have more accurate climate change beliefs, however, this relationship is opposite in rural areas, where young rural dwellers are less aware of climate change [10]. Arguably, in rural areas agricultural experience gained with time provides knowledge about changes in the climate cycle [38,46]. Finally, race only appears to have a consistent influence on climate change beliefs in North America, where non-white individuals show more concern and a higher risk perception than whites, a phenomenon known as white-male effect [9,42,47]. Nevertheless, this effect is not generally supported by cross-country evidence [10]. In conclusion, evidence about demographic effects on CCBs remains elusive, and these effects seem largely eclipsed by the aforementioned information approaches [10,18].

The discussion above identifies multiple factors that shape individual climate change beliefs. However, little research has included African countries in their analysis [11,12,46]. Those that do often include a limited number of predictors, which in turn, limit the understanding of what shapes CCBs in the African continent. This study aims to fill these gaps within the literature.

Research design

Methods

We analyse what shapes climate change beliefs in Africa using a random forest approach [48]. Random forest is a machine-learning approach that uses non-parametric recursive partitioning to produce models with high predictive accuracy [11,49]. It can handle high-dimensional (large number of predictors) multilevel datasets with high-level interactions and non-linear relations [50], so it is ideal for our dataset. For each dependent variable, we grow a random forest composed of 1,000 trees with a minimum node size of five, using the *ranger* package in R [51]. To the best of our knowledge, this is the first study to jointly combine survey and climate data at the second administrative level to explore what shapes climate change beliefs across 33 African countries.

Despite its advantages, random forest models are not easily interpretable on their own. To interpret them, we use some additional measures. First, we compute the variable importance measure, which 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 impurity importance, at a similar computational cost [52]. This measure shows which are the most important factors that shape CCBs. Second, 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 constant the rest of the variables. The code and data used for this analysis is available online.

Data

Dependent variables

Data for our dependent variables are drawn from the Afrobarometer [7]. We particularly use data from the latest round of surveys (R7), conducted between 2016 and 2018 —

the first time the Afrobarometer included climate change-related questions. The dataset is comprised of more than 45,000 observations from 33 African countries. The data is georeferenced at second-level administrative boundaries (see S1 for a detailed variable speciation). This allows us to overlay our climate variables to the same areas where the Afrobarometer surveys were conducted.

We include five different dichotomous specifications for climate change beliefs Our first specification, climate change *awareness*, measures whether survey respondents have heard about the existence or climate change or not. Second, we account for the respondents' belief that *human activity* is the main cause behind the current changes befalling the world's climate. Third, we are interested on whether respondents developed a *risk perception* from a changing climate that is making life worse in their country. Our final two specification examine respondent's beliefs on whether climate change *needs to be stopped* and whether ordinary citizens can help mitigate against it— a variable known in the literature as *self-efficacy*.

Independent variables

We include 67 independent variables from the Afrobarometer. They account for access to information, education, political ideology, religion, economic conditions, demographics, and agricultural experience, as suggested by previous research. Descriptive statistics and their corresponding Afrobarometer questions and coding scheme are included in the S1 File.

Additionally, we include four climate variables to assess the impact of local climate change on CCBs. Our first three variables are precipitation, maximum and mean temperature anomalies from the CRU 4.0 dataset [53]. The time-series data is drawn from 0.5° x 0.5° gridded data of monthly precipitation and maximum and mean temperatures values. We overlay second-administrative level boundaries of Africa over these gridded data rasters, using the mean value of the grids each administrative unit intersects with. We generate our anomalies for each administrative unit by calculating the monthly deviation from the long-term (1961-1990) mean for that month and dividing it by the panel's standard deviation [54]. We then annualize these anomalies by averaging the monthly anomalies of the 12 months before each respondent was surveyed. Therefore, we end having long-term anomalies for precipitation and maximum and mean temperatures, for the year before the survey was conducted.

For improving the robustness of our analysis, we also include a measure of drought for each administrative unit. We employ the 3-months standardized precipitation evapotranspiration index (SPEI-3) from the SPEI 2.6 database [55]. Since SPEI is also presented as 0.5º x 0.5º gridded data, the data extraction procedure is identical to the other climate variables. However, as SPEI is already presented as deviations from a long-term baseline, to annualize them we take the average of the 12 previous months from the date the survey was conducted.

Results and discussion

In this section we present and discuss the empirical results from our random forest analysis on what shapes climate change beliefs in Africa. Some common patterns emerge from the analysis among the results from our five different models. We discuss these patterns by order of statistical relevance to each outcome variable. Fig 1 shows the main results for climate change awareness, belief anthropogenic climate change, and climate change-related risk perception.

[FIG 1]

Fig 1. Key predictors for climate change awareness, anthropogenic climate change, and climate change-related risk perception.

Top 15 predictors of climate change awareness (A), human causation of climate change (C), and risk perception (E). (B) Partial dependence plot (PDP) of gender (*female*), access to online news (*news tech*), being favourable to one-party rule (*authoritarian*), and perceived agricultural conditions (*agric. cond.*) about climate change awareness. (D) PDP of mean temperature anomalies (*temp. anom.*), precipitation anomalies (*precip. anom.*), trust in institutions (*trust* institutions), and access to online news (*news tech*) over belief in human causation of climate change. (F) PDP of belief in human causation of CC (*CC human cause*), perceived severity of drought (*drought percep.*), perceived agricultural conditions (*agric. cond.*) and being favourable to one-man rule (*authoritarian*) over climate change risk perception.

First, the importance of perceived agricultural conditions stands out. Respondents' who perceive worsening agricultural conditions show greater awareness and perceived risk, more support for stopping climate change, and are more likely to believe in anthropogenic climate change. Indeed, Fig 1E shows that perceived agricultural conditions are the main predictor for climate change risk perception. Arguably, the importance of the agriculture sector in terms of employment ―more than 50% of employees across Sub-Saharan Africa work in agriculture― makes agriculture a strong concern to African citizens [2]. Thus, perceiving how climate change is already affecting agriculture may reduce its psychological distance. Our results suggest that for Africans climate change is not a problem for *others* across space and time, but rather a phenomenon that is happening *here* and *now* and it is affecting personally [56]. However, this finding also poses a challenge. Climate change has uneven impacts, and agriculture in some regions may benefit from changes in local climate [2]. Those who perceive those improvements in agricultural conditions show less CCBs, making them less likely to support or take environmental action. This implies that policy makers should further highlight the global nature of climate change and its overall negative impacts on agriculture to raise CCBs, impulse individual adaptation, and mobilise public support.

Second, attributing climate change to human activity increases risk perception, support for mitigation, and self-efficacy (Figs 1 and 2). If climate change is unnatural, it is extraordinary and thus riskier. Also, if climate change is human induced, its impacts can also be mitigated by human action. Besides, believing it is human caused can increase personal responsibility and, therefore, induce corrective responses [5,57,58]. This points to the convenience of spreading and highlighting the human origin of climate change to impulse behavioural changes and mitigation strategies in Africa.

[FIG 2]

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

Top 15 predictors of need to stop climate change (A) and self-efficacy (C). (B) Partial dependence plot (PDP) of mean temperature anomalies (*temp. anom.*), belief in human causation (*CC human cause*), perceived worsening of agricultural conditions (*agric. cond.*), and perceived risk from climate change (*CC risk percep.*) over need to stop climate change. (D) Partial dependence plot of mean temperature anomalies (*temp. anom.*), belief in human causation (*CC human cause*), perceived risk from climate change (*CC risk percep.*) and being favourable to one-man rule (*authoritarian*) over self-efficacy

Fig 2 shows that risk perception is positively associated with self-efficacy and the need to stop climate change. While some previous studies in the United States and United Kingdom point to fatalism or climate despair [3,59,60] ―where higher perceived risks discourage self-efficacy and action support, the opposite seems to be true for Africa. This could be the result of motivated control ―feeling more empowered in order to feel safe from a greater risk [61], or increased personal concern with climate change [62]. Either way, explaining why climate change is a critical risk for Africa will not discourage the African public, but it might encourage policy support and personal action [5].

As suggested by previous research, access to information and education are good indicators for believing in anthropogenic climate change and being aware of it. However, both indicators show a slight negative effect when it comes to more affective dimensions such as risk perception or believing climate change must be stopped. The limited emotional salience of climatic information compared with personal experience or motivated reasoning may account for this divergence [26–28]. Nevertheless, it must be noted that the importance of information is contingent on language (Fig 1D). Not speaking French, English or Portuguese hinders the understanding of climate terminology, which frequently lacks accurate translations to African languages [16]. Greater efforts should be made to translate the nature, causes, and impacts of climate change to African languages.

Local changes in climate conditions are among the most important predictors across all models. Overall, they are more important than access to news, political ideology, or demographics (see Table 1). Previous research finds that *perceived* changes in local temperatures were the most important predictor of climate risk perception in some African countries [11]. Building upon these findings, this study shows that *actual* long-term anomalies in temperature, rainfall, and drought at second-order boundaries do more to shape individual climate change beliefs than the above mentioned. Attribute substitution and emotional salience may explain the importance of personal experience with local weather conditions for CCBs [26,36]. In fact, qualitative evidence suggests that some communities in Africa understand climate change not as a global phenomenon but a local one [16]. 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 [41]. 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 pool of worry hypothesis, households with fewer resources are the most concerned about the present and future effects of climate change. Climate change is a close and urgent concern for them, as their income and assets are the most vulnerable to climatic risks [56,63].

Political ideology also has a significant impact on CCBs in Africa. Authoritarian and intolerant ideologies lessen climate change awareness, risk perception, belief that it must be stopped and self-efficacy. Authoritarian and hierarchical values have been consistent and negatively linked to climate change beliefs in other regions of the world [10]. Ideology influences what information people access, and how they process and assimilate it [18–21]. Our findings imply that authoritarian individuals are more likely to disregard climate change to justify their support for maintaining the status quo. These findings also suggest that it would be convenient for policy makers to reshape environmental discourses to better engage the authoritarian public. To do so, environmental policy and individual action can be framed as patriotism, innovation, or prosocial behaviour [64], and the focus of risk communication can be on the possible effects of climate change on human security and public order [65] .

Like ideology, previous research has suggested that religion prompts motivated reasoning, shaping thus CCBs. Overall, declaring oneself religious is mostly insignificant to predict CCBs. However, we do observe some significant differences across religions in Africa: Catholic and Orthodox Christians are more likely to believe in the anthropogenic nature of climate change and that it must be stopped, while Sunni Muslims shows the opposite trend. These findings illustrate the importance of actively engaging religious leaders to communicate environmental messages, giving them the tools for doing so effectively [16,24].

Finally, we find that demographic variables such as gender or race have some importance for CCBs. We find an important gender gap for awareness, as well as slightly negative effects for other dimensions of climate change beliefs. Women are less likely to be aware of climate change, as previous case studies in Africa had suggested [16,45,66]. In this case, differences in access to climate information do not explain this gender gap, so further research should address this issue. Besides, we find ethnicity to be related to risk perception and self-efficacy. Overall, Black Africans show more concern and self-efficacy than other ethnic groups, among whom Arab Africans are the less concerned. Therefore, we cannot talk about a “white male” effect [47] because White Africans do not especially neglect risks (in contrast to Arab Africans) nor women show more concern, rather the opposite. Finally, age and agricultural experience are insignificant across all models, contradicting previous findings within the literature [38,46].

Conclusion

There is a lack of consensus within the literature for what shapes climate change beliefs and most studies conducted on this topic are usually limited to Western developed nations. Our results show several novel findings for what shapes climate change beliefs across 33 African countries. First, actual changes in local climate conditions are stronger predictors of climate change beliefs in Africa than access to information, political ideology, or demographics across different model specifications. Similarly, worsening perceptions of climate conditions for agriculture is a strong predictor for all five dimensions for climate change beliefs. Second, our analysis also reveals that authoritarian and intolerant ideologies overall decrease climate change beliefs. Third, not speaking French, English or Portuguese hinders the understanding of climate beliefs. Finally, there is a small but important gender gap across different dimensions. Combined, our results suggest that more different causal mechanisms underly climate change beliefs than previously assumed [11]. We strongly believe that in-depth case-studies should further examine the complex causal mechanisms that shape climate change beliefs across different African countries to improve our understanding in order to implement the best mitigation and adaptation strategies for the region.

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Supporting information

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