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Country-level conditions like prosperity, democracy, and regulatory culture predict individual climate change belief

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Decades after the scientific community agreed on the existence of human-made climate change, substantial parts of the world's population remain unaware or unconvinced that human activity is responsible for climate change. Belief in human-made climate change continues to vary strongly within and across different countries. Here I analyse data collected by the Gallup World Poll between 2007 and 2010 on individual attitudes across 143 countries, using a random forest model, to show that country-level conditions like environmental protection, civil liberty, and economic development are highly predictive of individual climate change belief. Individual education and internet access, in contrast, are correlated to climate change awareness, but much less to belief in climate change's anthropogenic causes. I also identify non-linear pattern in which country-level circumstances relate to individual climate change belief. The local importance of most predictors varies strongly across countries, indicating that each country has its relatively unique set of correlates of climate change belief.

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Decades after the scientific community agreed on the existence of human-made climate change, substantial parts of the world's population remain unaware or unconvinced that human activity is responsible for the global climate crisis. Although belief in human-made climate change varies strongly within and across different countries, the causes of the observed cross-national variation remain largely unknown[1]. Most existing analyses have focuses primarily on analyzing climate change attitudes across Western English-speaking democracies and paid little attention to the formation of climate change belief in the Global South[1]. Moreover, many studies scrutinized public attitudes within specific countries (like the US[2,3], Germany[4], or India[5]), examining how individual attributes such as political orientations, cultural values, and demographic traits explain within-country variation in climate change belief[6–8].

These studies have shown that climate change belief in the US and in Europe is strongly influenced by political orientations and by demographic characteristics. Here, younger age cohorts and females, as well as individuals with environmental and left-wing worldviews, are more likely to believe in human-made climate change than others[7,9–11]. Examining 25 nationally representative polls from different countries, Hornsey and colleagues[12] also observed that climate change belief is most strongly associated with political orientations and less with demographic characteristics like education, age, or gender. However, most of the nationally representative polls available to their study contained data from US-Americans, Australians, and Europeans. When some of the authors later collected original data in 24 geographically much more diverse countries, they discovered that globally, the political stance is not frequently correlated with climate change belief. While right-wing orientation and individualism strongly predict climate change denial in the US and other English-speaking countries, this relationship was insignificant or even reversed in most non-English speaking nations[13].

Although no other study has analyzed individual climate belief in a similarly diverse sample, research on climate change concern has shown similar cross-national variation in the way in which individual traits shape climate change attitudes. Lewis, Palm, and Feng, for example, find that political orientations and gender predict climate change concern fairly consistently across English-speaking Western democracies, but hardly anywhere else[14]. In an even broader study, Lee and colleagues analyzed data from 119 countries and found climate change concerns to be strongly influenced by education, climate change belief, and perception of local temperature changes[15]. However, they also observed a large variation in the prediction effects of these variables across different countries. Several other studies also reveal a substantial variation in the direction in which demographic traits, like age or gender, correlate with climate change concern. While women and younger age cohorts tend to be more concerned about climate change in English-speaking constituencies, the opposite is true in most African countries[14].

Although these findings imply that national circumstances strongly modulate the development of climate change attitudes, little is known about the specific magnitudes and forms in which country-level conditions influence individual climate change belief. Comparing average climate change belief across 128 countries, Knight found country-level climate change belief to be systematically higher in societies that are wealthier, better educated, left-leaning, and more vulnerable to climate impacts[16]. While this study suggests that country-level conditions influence climate change belief, the study's focus on country-level correlations does not allow to differentiate the effects from individual traits and societal circumstances. Moreover, the choice of using an OLS regression introduces a natural limit to a number of covariates that can be considered and assumes linear relationships between all variables, an assumption that is questionable given the observed heterogeneity in comparative analyses of climate change belief.

To advance the understanding of global climate change belief, I analyze how both individual-level and country-level conditions predict individual climate change belief across 143 countries. I use random forests, a method from machine learning because this technique allows examining a large set of mixed-type predictors, estimate country-specific prediction effects, and estimate relationships without biases introduced by non-linear relationships, non-parametric distributions, or endogenous relationships among covariates (see "Methods" section). The individual-level data were collected by the Gallup World Poll (GWP) between 2007 and 2010 and is representative of approximately 95 percent of the world's adult population aged 15 and above[17]. I operationalize climate change belief as being aware of climate change and believing that it is caused mainly by human activity. To differentiate between awareness-raising and epistemic processes, I analyzed two different model specifications: In the first specification, the model predicts the likelihood of being aware of climate change and believing in its human causes for all individuals in the whole population ($n = 373{,}649$). The second specification restricts the sample to individuals that have already heard of climate change ($n = 271{,}790$) and predicts whether these individuals believe that climate change is caused mainly by human activity. Hence, while the former specification estimates the relation of my predictors with both becoming aware of climate change and believing in it, the latter specification focuses exclusively on estimating the epistemic process of believing in climate change's anthropogenic causes.

I analyze the prediction effect of nine different country-level variables that were identified in previous studies as potentially influencing climate change belief and for which sufficient cross-national data was available. In particular, I examine whether the domestic presence of environmental NGOs (operationalized as environmental NGOs accredited to the United Nations Framework Convention on Climate Change[18]) and the domestic presence of climate scientists (operationalized as scientific contributions to the Assessment Reports of the Intergovernmental Panel on Climate Change[19]) predict individual climate change belief, as both actors are important climate change communicators[20–22]. I also analyze the role of economic development (as GDP per Capita[23]) and civil liberties (operationalized with Freedom House' civil liberty rating[24]) because qualitative studies indicate that mass media outlets in poor countries struggle to cover climate change[25,26] and that authoritarian states may repress the activities of environmental NGOs[27–29]. Moreover, I also estimate the degree to which exposure to climate change impacts[30–32] (measured with Global Adaptation Initiative's exposure index[33]) and fossil fuel dependency[34] (both in terms of per capita emissions[35] and in carbon intensity per GDP[36]) are associated with individual belief in human-made climate change. Finally, as norms on environmental protection and market regulation may influence individual receptiveness to climate change belief[12,37], I analyze how well country-level environmental protection (measured with Yale's Environmental Performance Indicator[38]) and market-liberalism (as in the Heritage Foundation's Economic Freedom Index[39]) predict individual attitudes.

I control for regional effects and for all individual-level variables collected by the GWP which may plausibly influence climate change belief. Here, I consider the respondent's age, gender, education, internet access, and place of living (rural or urban)[9,15]. Since local pollution can serve as a cognitive model for anthropogenic climate change, I also examine whether the individual experience of air or water quality is related to climate change belief[40,41].

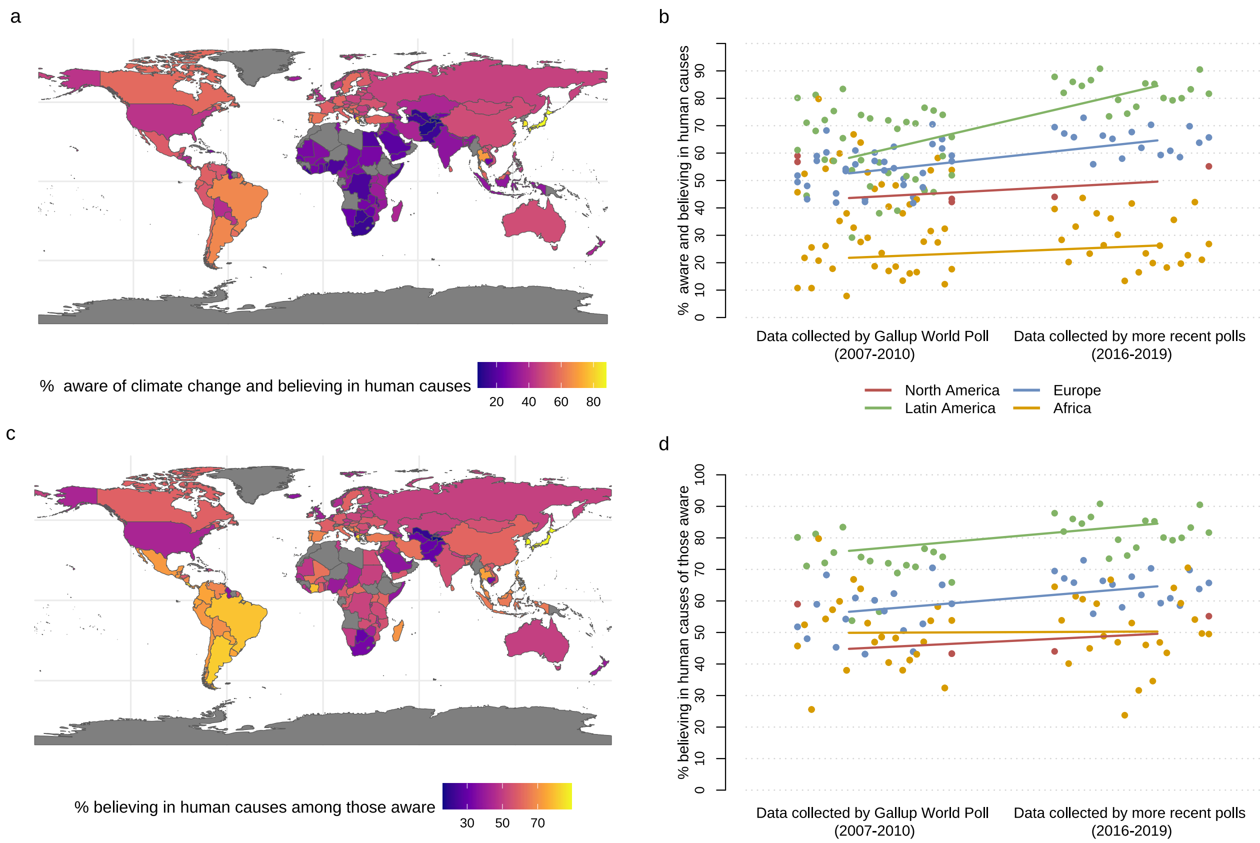

Fig. 1 Cross-national variation in climate change belief. Panel **a** displays the percentage of people that are aware of climate change and convinced that it is caused by human activity ($n = 373{,}649$), based on data from the GWP; **b** compares these estimates to data from seven more recent surveys; **c** visualizes the number of people believing that climate change is caused by human activity as a share from all respondents that are aware of climate change ($n = 271{,}790$, based on the GWP); and **d** compares these estimate to data from seven more recent surveys. Panels **a** and **c** use a blue to yellow color scheme to display the estimates and display countries with no data in gray. In panel c and d, individual countries are displayed as dots and regional averages are connected through lines. The dots and lines are colored according to world region with red indicating North America, blue Europe, green South America, and Yellow Africa.

Results and discussion

Climate change belief varies strongly across countries. According to data collected by the GWP, a third (28 percent) of the world population has never heard of climate change. From those who were aware of climate change, only around 60 percent believed that climate change is caused by human activity. Hence, only 42 percent of the world population were aware of climate change and convinced that it is caused by human activity. Climate change awareness and belief vary substantially across countries, ranging from just 8 percent in Liberia to 87 percent in Japan (Fig. 1a). Even after controlling for awareness, belief in the human causes of climate change remains unequally distributed across countries, from 15 percent in Tajikistan to 90 percent in South Korea (Fig. 1c).

Although more recent cross-country surveys cannot match the GWP in scope, they jointly suggest that the distribution of global climate change belief has not changed substantially in the latest decade. Comparing the GWP estimates to data from nationally representative polls conducted in Europe[42,43], North America[44,45], Latin America[46], and Africa[47] between 2016 and 2019, I find that climate change awareness and belief has further increased in Latin America, stayed moderate in North America and Europe, and remained low in Africa (Fig. 1b). Belief in climate change's anthropogenic causes has increased moderately in the Americas and Europe but remained virtually unchanged in Africa (Fig. 1d). Although differences in survey designs do not allow a reliable assessment of the development of climate change belief in specific countries, the overall trend in these recent polls indicates that cross-national variation continues to be substantial and that pre-existing regional patterns have likely persisted. Please see "Methods" section for details on calculation and the Supplementary Data 1 for numerical estimates.

For this article, I use a random forest model to analyze how well country-level conditions predict individual climate change beliefs as surveyed in the GWP. Random forest is a particularly suitable method for this analysis because it can estimate the relative prediction effect of a large number of mixed-type predictors without biases introduced by non-parametric distributions, non-linear relationships, or the presence of high-dimensional interactions among co-variates or multi-level clustered data[48–50]. Furthermore, it allows for the inductive exploration of the forms of association by estimating the way in which independent and dependent variables relate to each other without requiring prior assumptions about the functional form of their relationships[51]. One commonly cited disadvantage of random forests is that they are often difficult to interpret[52]. To increase the model's interpretability, I, therefore, apply various knowledge extraction techniques. Besides calculating the importance of each explanatory variable for correctly predicting climate change belief, I also estimate significance levels for all predictors, local prediction importance across different countries, and partial prediction effects of different values of the explanatory variables[53,54] (see "Methods" section for further details).

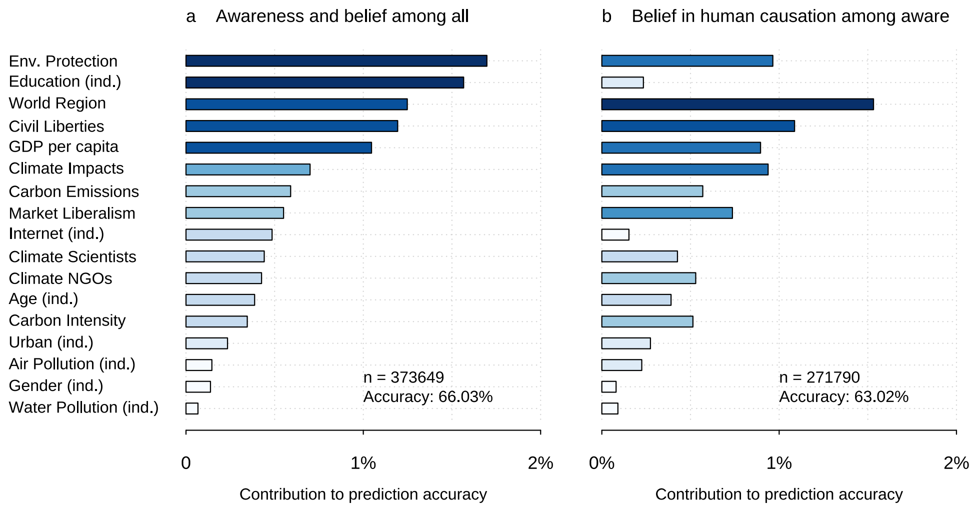

Fig. 2 Variable importance. The figure displays the importance of each explanatory variable for predicting (**a**) awareness and climate change belief in the full sample ($n = 373{,}649$) and (**b**) belief in the human causes of climate change among respondents who are already aware of climate change ($n = 271{,}790$). Variables denoted with "(ind.)" are measured on the individual level, all other variables on a country-level. The color of the bars corresponds with the level of importance with darker colors highlighting more important variables. All variables are statistically significant at a 0.1 percent level. World Region, Environmental Protection, and Civil Liberties are strongly related to climate change belief in both model specifications. Please see Supplementary Table 8 for a numerical representation of significance levels and importance measures.

Country-level conditions predict individual climate change belief. I find that all explanatory variables discussed in the introduction increase the accuracy of correctly predicting climate change belief at a 0.1 percent significance level in both model specifications. However, the prediction importance of the explanatory variables, measured in mean contribution to prediction accuracy, varies substantially. This prediction importance can be interpreted as the model's loss in predictive accuracy when the information of a given variable is removed from the model (see "Methods" section). In both specifications, country-level conditions are strongly predictive of individual beliefs. The most important variables for correctly predicting climate change awareness and belief (Fig. 2a) are country-level environmental protection, individual education, and world region; followed by civil liberties and economic development. The most important variables for correctly predicting belief in the anthropogenic causes of climate change among individuals already aware of climate change (Fig. 2b) are the respondent's world region, as well as country-level environmental protection, civil liberties, and exposure to climate impacts. Since most variables contain redundant information, the independent increase in prediction accuracy for every single variable lies below 2 percent. The gender of a respondent and their experience of air or water pollution is not important in any model specification.

The main differences between the results of the two model specifications are the importance of individual education and internet access. These two variables are highly and moderately predictive of climate change awareness and belief in the full sample (Fig. 2a), but only weakly correlated to belief in anthropogenic causes among individuals who are already aware of climate change (Fig. 2b). Country-level exposure to climate impacts, carbon-intensity, and market liberalism is more predictive of belief in anthropogenic causes than of awareness and belief combined. These results indicate that education and internet access might be decisive to stimulate climate change awareness, whereas exposure to climate impacts and a country's regulatory culture and carbon-intensity are more important for shaping individual belief in climate change's anthropogenic causes. Unlike awareness, climate change belief is almost exclusively predicted by country-level circumstances. Individual traits such as education, place of living, age, and gender contain little relevant information for correctly identifying belief in climate change's anthropogenic causes across individuals from 143 countries.

Some prediction effects are non-linear. Figure 3 visualizes a non-randomized recursive partitioning tree model in order to exemplify how the most important explanatory variables are related to climate change belief (see "Methods" section). The results of the inference tree model demonstrate that people are most likely to be aware of climate change and convinced of its anthropogenic causes when they have obtained at least secondary education and live in East Asian environmentally friendly countries (Fig. 3, terminal node 8). Individuals who have not obtained a secondary education and live in South Asian or Sub-Saharan countries with state-controlled economies are the least likely to believe in human-made climate change (Fig. 3, terminal node 12).

Identifying the direction in which an explanatory variable predicts climate change belief in the random forest model is complex because the model allows the prediction direction to change at each node of the underlying inference trees, conditional on the specific correlations in local subsamples. In order to recover the global prediction direction of each explanatory variable over the whole random forest model and over the whole sample, I calculate partial variable predictions. Partial variable predictions are calculated by estimating the average prediction effect (in terms of likelihood of climate change belief) for different values of explanatory variables while integrating out the effect of all other variables at these positions (see "Methods" section).

The overall direction in which most explanatory variables related to climate change belief is consistent with theoretical expectations: climate change belief tends to be higher among younger people (by approximately 3 percent) and those living in urban areas (by 2–3 percent). Higher education and internet access are associated with a 16 percent and a 7 percent increase in being aware of climate change and believing in it. However, among those who are already aware of climate change, higher education and internet access increase predicted climate change belief only by 3 percent and 1 percent, respectively. Across all

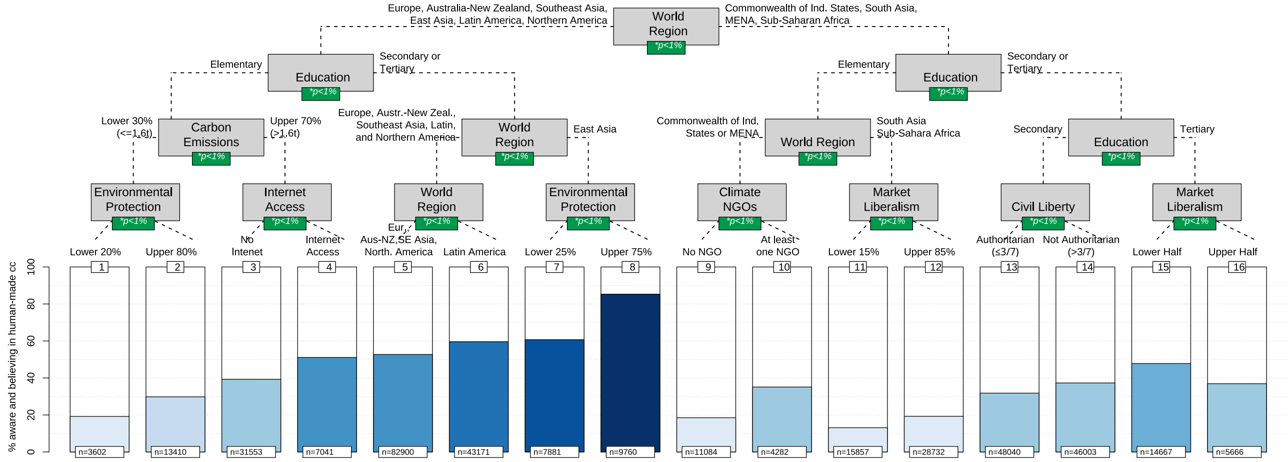

Fig. 3 Recursive partitioning tree model on climate change belief. The gray boxes are inner nodes on which splitting decisions are made. The green boxes indicate the significance level of the respective splitting decision. The bars at the bottom, called terminal nodes, display the share of respondents that are aware of climate change and belief in its anthropogenic causes ($n = 373{,}649$). The results of the recursive partitioning model indicate that people who live in environmentally-friendly East Asian countries and have a secondary or tertiary education degree are the most likely to believe in anthropogenic climate change.

countries, men are slightly more likely to believe in human-made climate change than women (by 2–3 percent). Self-reported air and water pollution are associated with marginally higher levels of climate change belief (approximately 1 percent and less than 1 percent, respectively).

Country-level conditions that predict higher levels of climate change belief are country-level environmental protection (by 7–11 percent), civil liberties (by 7 percent), exposure to climate-impacts (by 4–7 percent), and the number of domestic NGOs and climate scientists (both 1–2 percent). Higher levels of carbon intensity, in contrast, predict lower levels of individual climate change belief (by 1–2 percent).

The model results reveal strong regional effects. Respondents from East Asia and Latin America are more inclined to believe in human-made climate change (by 4–5 percent) while living in Sub-Saharan Africa and in former Soviet countries is associated with lower levels of climate change belief (up to 3 percent). Please see the Supplementary Figs. 3–8 for details on the partial predictions of all variables in both model specifications. The absence of systematic cross-regional analyses makes interpreting these regional effects difficult. Qualitative studies suggest that limited mass media capacity could partly explain the negative regional effect of living in Sub-Sahara Africa[55]. Other case studies indicate that the positive effect of living in East Asia may be partly attributed to the proactive role of East Asian governments in communicating climate change[56–58], while capable civil society organizations and a widespread depoliticization of global warming may be responsible for the strong effect of living in Latin America on believing in human-made climate change[59–63].

Lastly, I find economic development, market liberalism, and per capita carbon emissions to be non-linearly related to climate change belief (Fig. 4). The relationship of all three variables with climate change belief is bell-shaped, meaning that moderate values predict the highest levels of climate change belief. Predicted climate change belief increases by 4–6 percent with increasing economic development up until approximately 30,000 $ USD in purchasing power parity. After this approximate threshold, additional increases in economic development are associated with decreasing values of climate change belief (by up to 2 percent; Fig. 4a). Likewise, market liberalism is positively correlated with climate change belief up until an index value of sixty (which is the median value of all countries in the sample). Above this threshold, the predicted belief in the anthropogenic causes of climate change decreases by approximately 3 percent (Fig. 4b). One interpretation of these observed non-monotonous relationships is that economic development and market liberalism may foster climate change belief up until a certain threshold because both variables promote the proliferation of the mass media quality necessary to broadcast climate change[25,26,64]. This positive effect might diminish once mass media quality is sufficiently saturated. Excessive degrees of economic wealth and market liberalism might be negatively correlated to climate change belief because of an accentuated system justification bias among individuals from wealthy countries (who have higher incentives to justify their status-quo) or because of a higher density of (climate denialist) libertarian thinktanks in market-liberal economies[65–67].

Similarly, I find carbon emissions to be positively related to climate change awareness and belief up until annual emission levels of approximately 5t of CO_2 per capita. Above this threshold, increasing carbon emissions are associated with decreasing levels of climate change belief. The negative effect is stronger in the specification that estimates belief in anthropogenic causes among people that are already aware of climate change (Fig. 4c). A potential interpretation of the positive relationship may be that some fossil fuel production is helpful to direct public attention to anthropogenic climate change. This interpretation is consistent with existing studies showing higher climate change coverage in countries with more carbon emissions[20] and other studies finding higher environmental awareness among individuals living close to coal mining regions[68]. The negative correlation could be explained by an accentuated self-serving and system-justification bias among people from countries with excessive carbon emissions[13,34]. I also find the observed non-linear prediction effects of market liberalism and carbon emissions to be substantially stronger when estimated in combination with economic development, a finding that suggests strong interaction effects among these variables. Market liberalism and carbon emissions can—jointly with economic development—account for up to 15 percent of the variation in the probability of believing in human causes among people who aware of climate change (see the Supplementary Discussion).

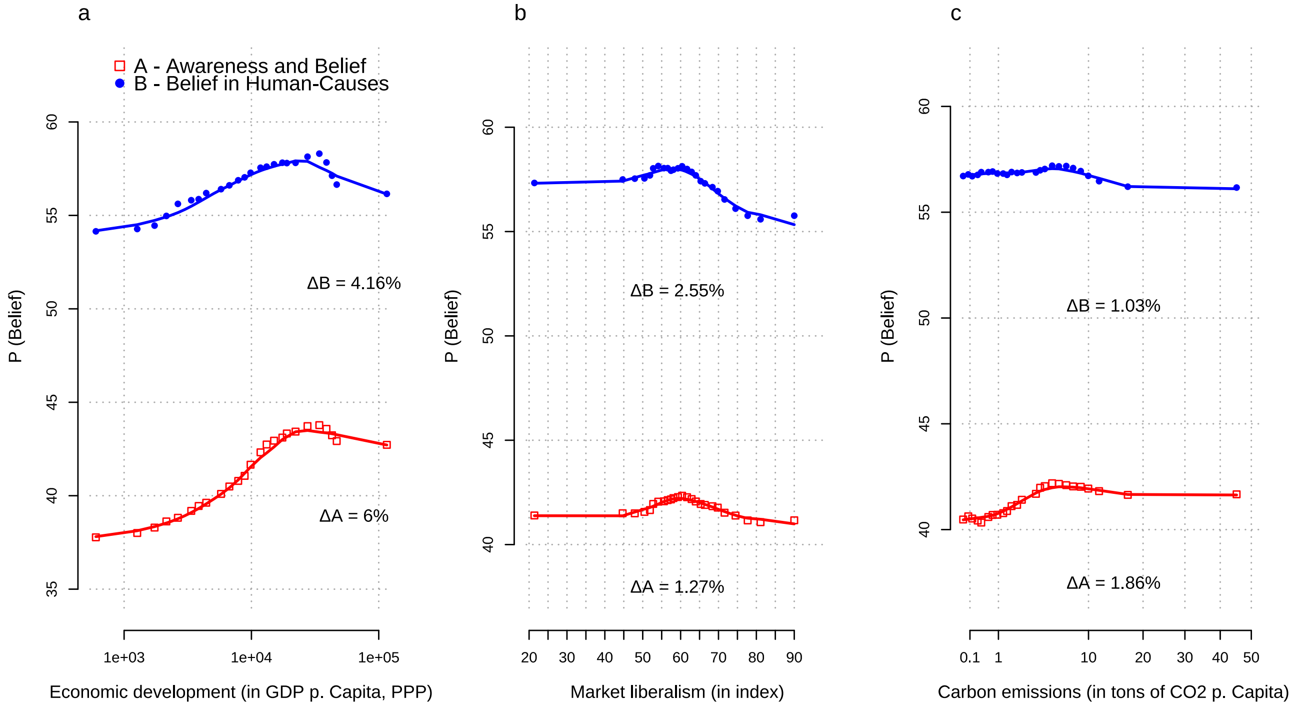

Fig. 4 Non-linear forms of correlation. I find that (**a**) economic development, (**b**) market liberalism, and (**c**) fossil fuel emissions are related in a bell-shaped form to climate change belief. For all these variables, moderate values predict the highest probability of belief in human-made climate change. The *x*-axis in panel **a** is log-transformed because economic development is distributed highly unequally. The *x*-axis in panel **c** is square root-transformed because most countries emit less than ten tons of CO_2 per capita and year.

Strong variation in predictor importance across countries. Finally, I find that the local importance of the predictors varies strongly across different countries. The local importance hereby measures the frequency in which individual observations become misclassified when an explanatory variable is permutated (see "Methods" section). The model identifies environmental protection as the most important variable for correctly predicting climate change awareness and belief in most countries (in 44 from 143 countries); followed by individual education (most important in 38 countries) and world region (most important in 35 countries). World region is most frequently the decisive variable for correctly predicting belief in human causation among respondents that are already aware of climate change (in 53 from 143 countries); followed by GDP per capita (most important in 19 countries) and market liberalism (most important in 14 countries). Please see the Supplementary Data 1 for a full list of the local importance of all predictors, all countries, and both model specifications.

Figure 5 visualizes the local importance of four of the most important variables for predicting climate change awareness and belief. Figure 5a shows that country-level environmentalism is particularly predictive of climate change belief in Japan, but also in countries with poor environmental protection such as South Africa and the Democratic Republic of Congo. Interpreting this cross-national variation in predictor importance remains difficult. Qualitative studies suggest that that the importance of environmental protection for climate change belief in Japan could be explained with the pronounced role of environmental institutions in raising climate change awareness in Japan[69]. The correlation between poor environmental protection and limited climate change belief in South Africa may reflect the country's widespread prioritization of fossil-fuel driven economic development over ecological concerns and the limited credibility of traditional environmental NGOs in the country[70,71]. Formal education is very important for identifying climate change beliefs in China, Latin America, and some African countries. It is less important in North America and Europe (Fig. 5b). These results are consistent with existing studies that characterize education as a crucial condition for climate change belief in China, but as irrelevant or even counter-productive for inspiring climate change belief in the United States[15,72,73]. Figure 5c indicates that regional effects are most important for correctly predicting climate change belief in the Middle East, Central Asia, and in East Asia. Civil liberties are most predictive of individual beliefs in autocratic or semi-autocratic countries like Saudi Arabia, Egypt, or Turkmenistan (Fig. 5d).

Summary of results and implications for future research. The results show that country-level circumstances such as economic development, civil liberties, and environmental protection are highly predictive of individual climate change beliefs. In particular, this is the first study that finds significant and substantial correlations between civil liberties and climate change belief and between the domestic presence of NGOs and scientists and individual climate change belief. I also find individual education and internet access to be strongly predictive of climate change awareness, but much less predictive of belief in climate change's anthropogenic causes. Moreover, this analysis discovers novel non-monotonous patterns in which economic development, market liberalism, and carbon emissions are related to individual climate change beliefs. The results thereby suggest that the relationships of these three variables with climate change belief may be more complex than previously assumed and that the observed correlations may reflect multiple overlapping and partly contradicting causal processes. Finally, the observed heterogeneity in predictor importance across different countries indicates that each country has its relatively unique set of correlates of climate change belief. This observation is consistent with results from similar studies that show that the magnitudes and directions in which individual traits influence climate change concern vary strongly across countries and regions[13–15]. Future quantitative

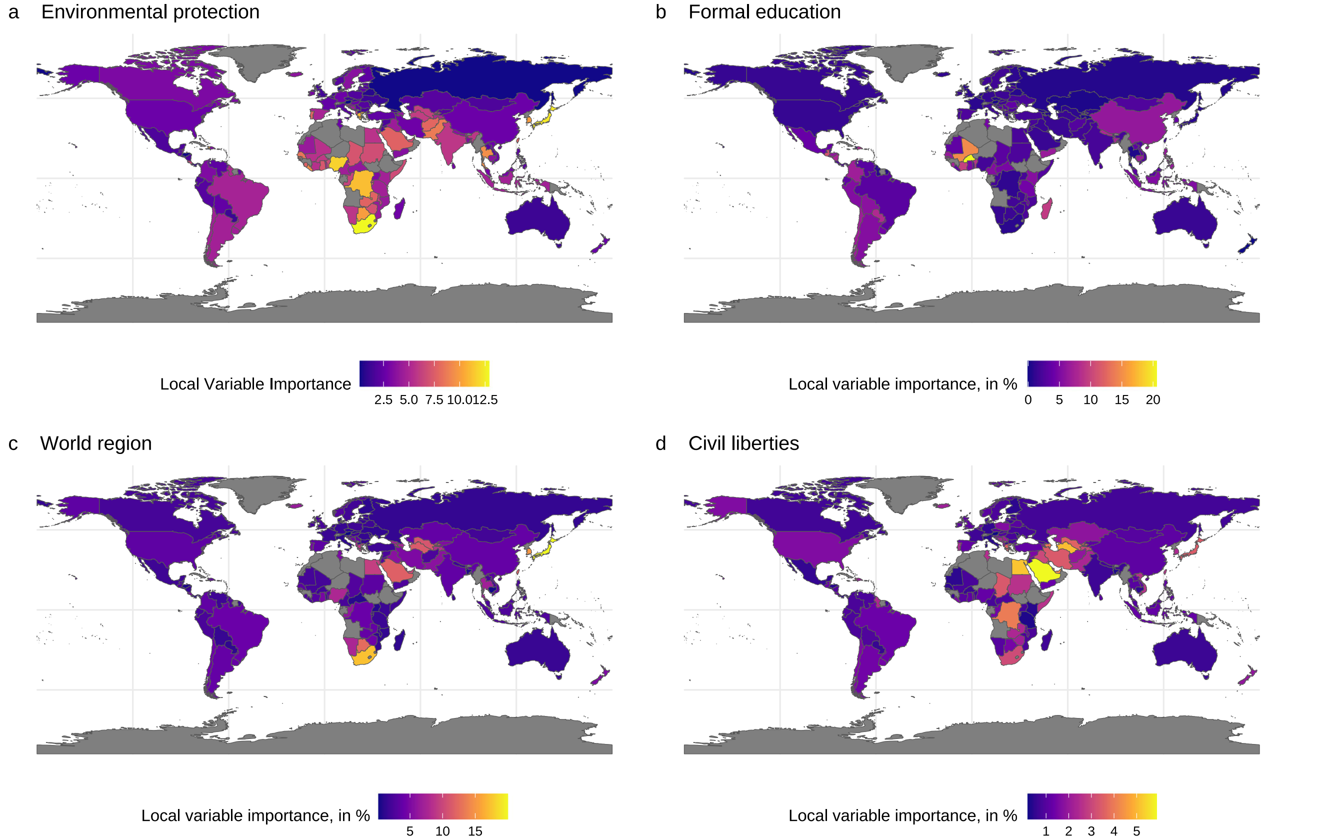

Fig. 5 Local importance for predicting climate change awareness and belief. The figure visualizes the frequency in which individual observations ($n =$ 373,649) get misclassified when (**a**) environmental protection, (**b**) formal education, (**c**) world region, and (**d**) civil liberties are randomly permutated. The local importance of these predictors varies strongly across different countries.

analyses should further examine how individual and country-level conditions interact in predicting individual climate change beliefs. Moreover, more within-case studies and cross-regional comparative analyses are necessary to interpret the observed correlations and to understand how public belief in human-made climate change develops in countries other than English-speaking Western democracies.

Methods

Data collection and operationalization. This article draws on data collected in multiple waves of the Gallup World Poll (GWP) between 2007 and 2010. This dataset is representative of the adult population of 143 countries which together represent more than 99 percent of the world population. Please see Supplementary Data 1 for the sample sizes of each country. The GWP includes information from respondents that are usually not featured in other surveys, such as people living in remote and hard-to-reach areas, illiterate people without access to telephone and internet, and respondents from countries with active conflicts. For countries in which the interviews were conducted face-to-face, sampling units were stratified by population size or geography with clusters at one or multiple stages. When population information was available it was used to select samples proportional to population size, otherwise, the selection was purely random. For countries in which interviews were conducted by phone, Gallup used random-digit-dialing or a nationally representative list of phone numbers. Post-stratification weights were constructed on the basis of gender, age, and if reliable data were available, education, and socioeconomic status.

I operationalize my dependent variable, belief in human-made climate change, as having heard of climate change and believing that it is caused by human activity. More specifically, I consider people as believing in human-made climate change if they responded with “A result of human activities” to the survey question “Temperature rise is a part of global warming or climate change. Do you think rising temperatures are…?”.

All individual-level explanatory variables were collected in the same survey as the dependent variable. I supplemented the individual observations with country-level information. Here, I used data from the World Bank for GDP per Capita[74], per capita carbon emissions[75], and carbon intensity per unit of GDP[76]. I operationalized the domestic presence of climate scientists with the number of national contributions to the 4th Assessment Report of the IPCC[77]. Likewise, approximate the domestic presence of climate NGOs in each country by using data on the number of environmental NGOs accredited to the UNFCCC[78]. I use data from Freedom House to measure civil liberties[79] and data from the Heritage Foundation to operationalize market liberalism[80]. Finally, I draw on data from the Yale Environmental Performance Indicator to capture country-level environmental protection and on data from the Global Adaptation Initiative to quantify country-level exposure to climate change impacts. For all observations, I used the country-level from one year before the collection of the individual data to allow a one-year time lag for societal conditions to materialize on the individual level. For the country-level data on the accreditation of climate change NGOs to the UNFCCC, I use data from 2015 because no earlier data is available. Please see Supplementary Table 6 for a descriptive analysis of all independent variables used in this paper.

Data processing. In preparation for this analysis, I excluded all respondents from the survey who displayed problems in understanding the question on climate change awareness by responding with “refusal” or “don’t know” to the question whether they have heard of climate change or global warming (34,036 from originally 407,685 respondents). Afterward, I approximated missing values in the explanatory variables where ancillary data was available and imputed all remaining missing values with iterative multiple imputation techniques (see Supplementary Tables 4–5). I also calculated a robustness test with case-wise deleted data in which all results remain robust (see Supplementary Tables 9–10). Furthermore, I weighted the data with scaled post-stratification weights that correct for sampling biases and for differences in sample size across countries. The weights in the central model ensure that each country in this analysis has “one vote”. This weighting strategy is therefore particularly suitable for cross-country inferences. I also calculated a robustness check-in which I scaled the weights by population estimates. These population-scaled weights give respondents from more populous countries a proportionally higher influence on the model results. The main results also remain robust in this specification (see Supplementary Methods).

Descriptive analysis. I estimated global climate change belief by using the GWP data and by applying population-scaled survey weights. The country-specific estimates in Fig. 1 were calculated using the post-stratification weighted GWP data. For the estimation of the recent values of climate change belief, I used data from the Yale Program on Climate Change Communication[81] for estimating climate change belief US and Canada (aggregated as North America), from the European Social Survey[82] and the European Investment Bank[83] for estimating belief in 17 European countries (aggregated as Europe), from the Latinobarómetro for estimating belief in 18 Latin American countries (aggregated as Latin America), and from the Afro-barometer for estimating belief in African 23 countries (aggregated as Africa). Country-specific estimates are reported in sheet 1 in the Supplementary Data 1. Please note that the calculated estimates are used to demonstrate the prevalence of cross-national variation in climate change belief and of broad regional trends over the last decade. Given the differences in survey designs, the data are not suitable for comparing specific country estimates from the GWP to data from more recent surveys. Please see Supplementary Tables 1–3 and Supplementary Methods for further details.

Random forest analysis. This article uses a random forest technique to analyze the cross-national distribution of climate change belief. Random forests are a versatile machine learning technique that uses randomized recursive partitioning to solve complex prediction, regression, and classification problems[48,84]. They draw on ensembles of recursive partitioning tree models, exemplified by the non-randomized partitioning tree model displayed in Fig. 3 (which was implemented with the *party* package in R). Random forests fit a high number of single partitioning tree models and inject elements of randomization in each of them, which has proven to substantially increase the overall model's predictive performance vis a vis new data. This high degree of predictive performance is responsible for the popularity of random forests in genetics and neuroscience and has also led to a growing application of the method in the social sciences[85,86].

Random forests offer two distinct advantages over conventional regression techniques. First, they are wildly compatible with different types of data and relationships. In particular, they can estimate the effect of a large number of mixed-type predictors, can operate comfortably under non-parametric distributions, and are able to capture complex non-linear relationships, even under the presence of high-dimensional interactions among co-variates and multi-level clustered data[48,49,87]. This versatility of random forests allows for the analysis of a large number of partly interrelated predictors of climate change belief without risking overfitting or biases introduced by relationships among my covariates. Second, random forests are able to inductively explore relationships by estimating the pattern in which independent and dependent variables relate to each other without requiring prior assumptions about the functional form of these relationships[88]. Random forest's inductive abilities hence enable a review of the functional form of the proposed relationships and to discover novel non-monotonous patterns in which societal conditions relate to climate change belief. A commonly cited disadvantage of random forests is their limited interpretability. Many argue that it is difficult to use random forests to "explain" certain outcomes (as opposed to predicting them) because random forests operate, like all machine learning techniques, in a black box[52]. However, over the last years several ancillary techniques, like partial prediction effects, were developed that increasingly allow one to "whitebox" random forest results and to retrieve information on properties like the functional forms and the direction in which explanatory variables relate to outcome variables[54,89].

I calculate four metrics from the random forest model. First, I estimate the mean contribution of each explanatory variable to the model's prediction accuracy. This metric, often called "variable importance", describes the added value of an explanatory variable for correctly predicting an outcome variable[90]. I calculate this variable importance with the *randomForestSRC* package using the computationally optimized "random" algorithm for the calculation of the variable importance[91]. Please see Supplementary Table 8 for numerical representations of the importance levels that are displayed in Fig. 2.

Second, I conduct a permutation-based significance test, which is a (two-sided) significance test that estimates the likelihood that the variable importance results purely from random chance. In this test, the real variable importance is compared to the distribution of variable importance under the Null hypothesis of no association, which is generated by fitting the model around a thousand times while randomly permutating the response variable[92]. I have calculated the distribution of the Null hypothesis and the significance levels using the package *rfPermute*[93]. Please see Supplementary Table 8 for numerical representations of the calculated significance levels of all predictors.

Third, I analyze the overall form and direction in which each explanatory variable relates to the outcome variable with a technique called partial variable predictions. This technique allows examining the form in which an explanatory variable is related to an outcome variable by calculating n predictions of the outcome variable on n evenly spaced-out values of an explanatory variable while integrating out the effect of all other co-variates at this position[89,94]. I calculate the partial variable predictions using the *randomForestSRC* package[95]. Please see Supplementary Figs. 3–7 for visual representations of partial variable predictions for each explanatory variable.

Fourth, I calculate the local predictor importance for every single observation and aggregate this local predictor importance to the national level. Local importance is a statistical metric of random forests that measures the average times a specific observation is misclassified when a given explanatory variable is randomly permuted[84]. I calculate the local importance of each variable with the *randomForest* package[84]. For more details on the random forest model, the ancillary techniques used in this paper, and for extended results of the central model, the ancillary analyses, and the robustness test please see Supplementary Figs. 1–2, Supplementary Tables 7–10, and the Supplementary Methods.

Figures. All figures were created in R using the base functions and the packages *grid*, *gridBase*, *gridExtra*, *ggplot2*, *rnaturalearth*, *sf*, and *plot3D*.

Data availability

The data generated for all descriptive and inferential analyses in this paper are made available at a public repository (https://doi.org/10.17605/OSF.IO/3BG2Z) The descriptive data on climate change belief per country and the estimated local variable importance measures are also available in the Supplementary Data 1. The raw data underlying the inferential analyses come from the Gallup World Poll. They are available from Gallup but restrictions apply to the availability of these data, which were used under license for this study. These raw data are not publicly available but can be obtained from the corresponding authors upon reasonable request and with permission of Gallup. The Gallup World Poll can also be purchased here: https://www.gallup.com/ The raw data underlying the descriptive analyses of climate change belief in Africa, Europe, North America, and South America between 2016 and 2019 are publicly available. Detailed information about these data and their sources are provided in the "Methods" section.

Code availability

An annotated script containing the code used to generate the findings of this study is available at a public depository (https://doi.org/10.17605/OSF.IO/3BG2Z).

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