Predictors of public climate change awareness and risk perception around the world

Tien Ming Lee[1,2]★[†], Ezra M. Markowitz[3,4,5], Peter D. Howe[2,6], Chia-Ying Ko[2,7,8] and Anthony A. Leiserowitz[2]★

Climate change is a threat to human societies and natural ecosystems, yet public opinion research finds that public awareness and concern vary greatly. Here, using an unprecedented survey of 119 countries, we determine the relative influence of socio-demographic characteristics, geography, perceived well-being, and beliefs on public climate change awareness and risk perceptions at national scales. Worldwide, educational attainment is the single strongest predictor of climate change awareness. Understanding the anthropogenic cause of climate change is the strongest predictor of climate change risk perceptions, particularly in Latin America and Europe, whereas perception of local temperature change is the strongest predictor in many African and Asian countries. However, other key factors associated with public awareness and risk perceptions highlight the need to develop tailored climate communication strategies for individual nations. The results suggest that improving basic education, climate literacy, and public understanding of the local dimensions of climate change are vital to public engagement and support for climate action.

Despite the widespread scientific conclusion that global climate change is happening, mostly human-caused, and a serious risk, public understanding of these facts and support for climate change policies is more equivocal worldwide[1–3]. Climate policy action in most countries will depend on gaining and maintaining public support for a diverse portfolio of societal changes[4]. Recent research on public perceptions of climate change has improved our understanding of the lay public's evolving response[5,6]. Levels of climate change awareness, knowledge, perceived risk, and support for mitigation or adaptation vary greatly across the world[1,3]. So far, numerous factors have been identified—including experiential, physical, psychological and socio-cultural variables—that influence individual- and/or group-level responses to climate change[7–9]. Much of this work has focused on individuals' risk perceptions regarding the potential impacts of climate change on themselves, their families and their communities, which in turn influence individuals' policy preferences, civic engagement, adaptation behaviour, and other important responses[10,11].

Current research on public perceptions of climate change, however, has been dominated by studies in Australia, the United States and Europe[6,12,13]. Although these findings have greatly advanced our understanding of the complexity of climate change belief and risk perception, they may be country- and culture-specific and thus difficult to generalize across a geographically, economically and culturally diverse planet. At the same time, relatively little research has explored cross-national differences in climate change risk perceptions (but see ref. 14). Further, sociological research suggests that contextual factors and processes can be powerful forces shaping how individuals and communities engage with the issue[15]. Indeed, national differences in climate change risk perceptions may help explain the differing levels of political support across countries for climate action. Yet, at present we lack even a rudimentary understanding of the factors shaping citizens' climate change awareness and risk perception globally, owing to past data unavailability.

Here, using data from the largest cross-sectional survey of climate change perceptions ever conducted, we provide the first global assessment of the factors underlying both climate change awareness and risk perception. The data come from the Gallup World Poll, conducted in 2007 and 2008, from nationally representative samples in 119 countries, representing over 90% of the world's population[16]. In this study, we classify a respondent's awareness level as either 'aware' or 'unaware' of climate change. For those who are 'aware', we further assess the level of climate change risk perception by grouping responses to the question, 'How serious of a threat is global warming to you and your family?', into two categories: 'serious' and 'not serious'. The total sample size of the risk perception analysis is thus smaller owing to relatively low levels of climate change awareness in some countries (for example, 65% of respondents were unaware of climate change in India). Therefore, this analysis identifies only the best predictors of risk perception among the subset of 'aware' respondents.

Using additional variables collected by the Gallup World Poll, we explore the relative influence of individual-level factors in shaping

[1]Earth Institute, Department of Ecology, Evolution and Environmental Biology, and Center for Research on Environmental Decisions, Columbia University, New York, New York 10027, USA. [2]Yale Project on Climate Change Communication, School of Forestry & Environmental Studies, Yale University, New Haven, Connecticut 06511, USA. [3]Earth Institute and Center for Research on Environmental Decisions, Columbia University, New York, New York 10027, USA. [4]Princeton Institute for International and Regional Studies, Princeton University, Princeton, New Jersey 08544, USA. [5]Department of Environmental Conservation, University of Massachusetts, Amherst, Massachusetts 01003, USA. [6]Department of Environment and Society, Utah State University, Logan, Utah 84322, USA. [7]Department of Ecology and Evolutionary Biology, Yale University, New Haven, Connecticut 06520, USA. [8]Research Center for Environmental Changes, Academia Sinica, Taipei 11529, Taiwan. [†]Present address: Program in Science, Technology and Environmental Policy, Woodrow Wilson School of International and Public Affairs, Princeton University, Princeton, New Jersey 08544, USA. ★e-mail: tienminglee@gmail.com; anthony.leiserowitz@yale.edu
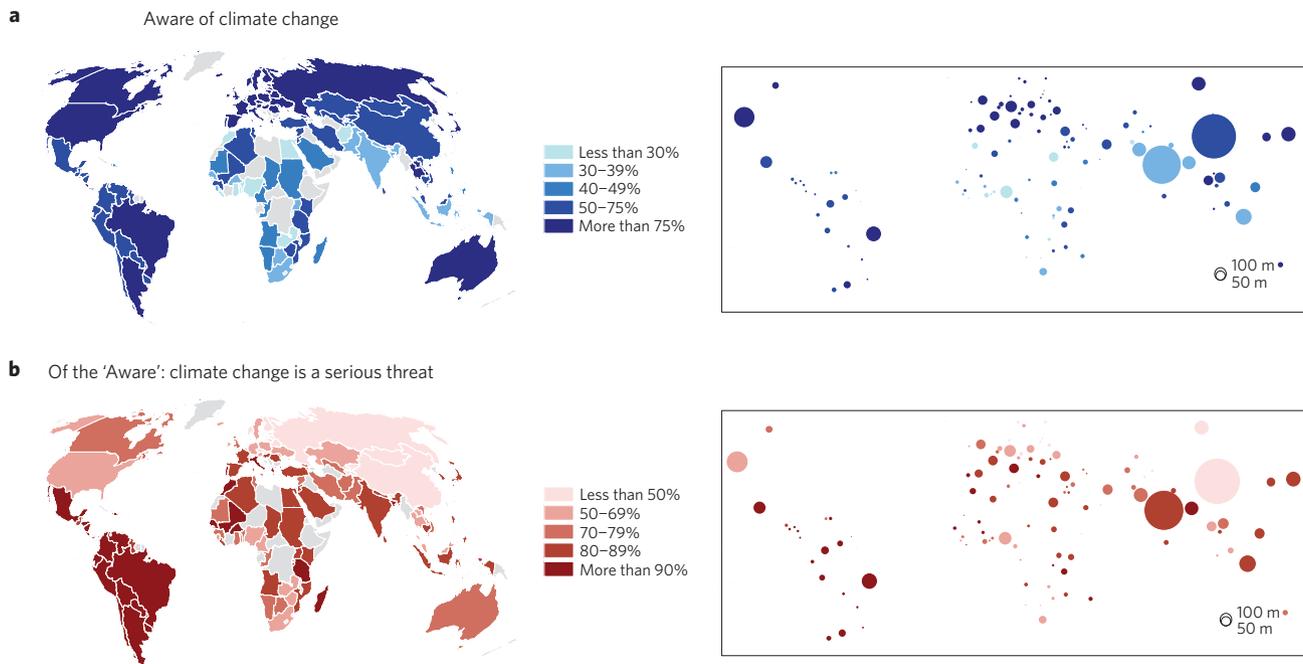
Figure 1 | Geographic patterns of global climate change perceptions opinion poll. Geographic patterns of natnal climate change perceptions opinion poll in 2007–2008 worldwide (N=119) on the percentage of awareness (**a**) and risk perception (**b**). Data is weighted and collected by Gallup on the basis of two questions: How much do you know about global warming or climate change? And for those who are aware, they were further asked: How serious of a threat is global warming to you and your family? Left, Original responses were recategorized into binary level and as a percentage for each nation. For clarity, the level of awareness and seriousness are shown in five colour classes. Areas in light grey represent countries with no data. Right, Perception patterns with respect to adult (15 years and older) population sizes, using the same colour classification. Bubble size for each country is proportional to adult population size, where large values indicate large populations. The location of each bubble approximates the spatial relationships among the countries.

climate change awareness and risk perception among individuals in each nation. These variables include socio-demographics (for example, gender, age, religion, education and location)[13,17], physical[18] and financial[19] well-being, beliefs related to climate change (for example, the primary cause of climate change)[8,20], communication (media) access, behaviours (for example, pro-environmental and civic engagement)[21], and opinions on related issues (for example, satisfaction with local air and water quality)[22] (see Methods for details).

On the basis of previous findings, we hypothesize that education level will be the most important (that is, top-ranked) predictor of climate change awareness, while understanding that global warming is human-caused will be the most significant predictor of perceived risk[8,20]. With the rapid spread of communication devices and channels globally, we also expect awareness of climate change to be greater among individuals who score higher on an index of communication access. Because the perception of local temperature changes seems to be relatively accurate worldwide[23] and experiences with local temperature can influence climate change belief[24,25], we hypothesize that the perception of recent local temperature change will predict risk perception. Further, we hypothesize that gender, age and location will also predict risk perceptions[13,26]. We also test for a relationship between religion and risk perceptions, as has been observed with environmental concern more broadly[17]. Some members of the public in the United States interpret climate change using a mental model of air pollution[22], so we investigate whether perceptions of local air and water quality predict climate change awareness and risk perceptions.

Members of the American public who hold pro-environmental views, demonstrate high involvement with environmental policy issues, and show active civic participation are particularly concerned about climate change and the environment[21,27]. Thus, we hypothesize that, globally, members of the public that report more pro-environmental behaviours, who express dissatisfaction with preservation efforts by the government, and who indicate high levels of civic engagement will be more likely to be aware of and concerned about climate change. Finally, many studies suggest that climate change will have large negative impacts on human well-being[18], but few have considered how an individual's current state of well-being influences climate change risk perceptions (for example, effects of economic recession and health[19,28]). For example, people with low incomes and poor health may be more likely to be aware of and perceive climate change as a threat than individuals with high incomes and better health. As such, we hypothesize that current household income, financial well-being and physical health may affect climate change awareness and risk perceptions.

Diverse global public opinions of climate change

Similar to previous multinational public opinion polls[1–3], this study finds that climate change awareness and risk perception were unevenly distributed around the world in 2007–2008 (Fig. 1). The highest levels of awareness (over 90%) were reported in the developed world, including North America, Europe and Japan (Fig. 1a). By contrast, majorities in developing countries from Africa to the Middle East and Asia reported that they had never heard of climate change, including more than 65% of respondents in countries such as Egypt, Bangladesh, Nigeria and India. Among those respondents who had heard of climate change, however, those in developing countries generally perceived climate change as a much greater threat to themselves and their own family than did respondents in developed countries (Fig. 1b).

National, cultural and geographic factors play an important role in shaping individual-level perceptions of climate change[1,2,22], thus it is important to identify the key individual-level predictors of climate change awareness and risk perception for each country separately. In high-dimensional stratified data such as the Gallup
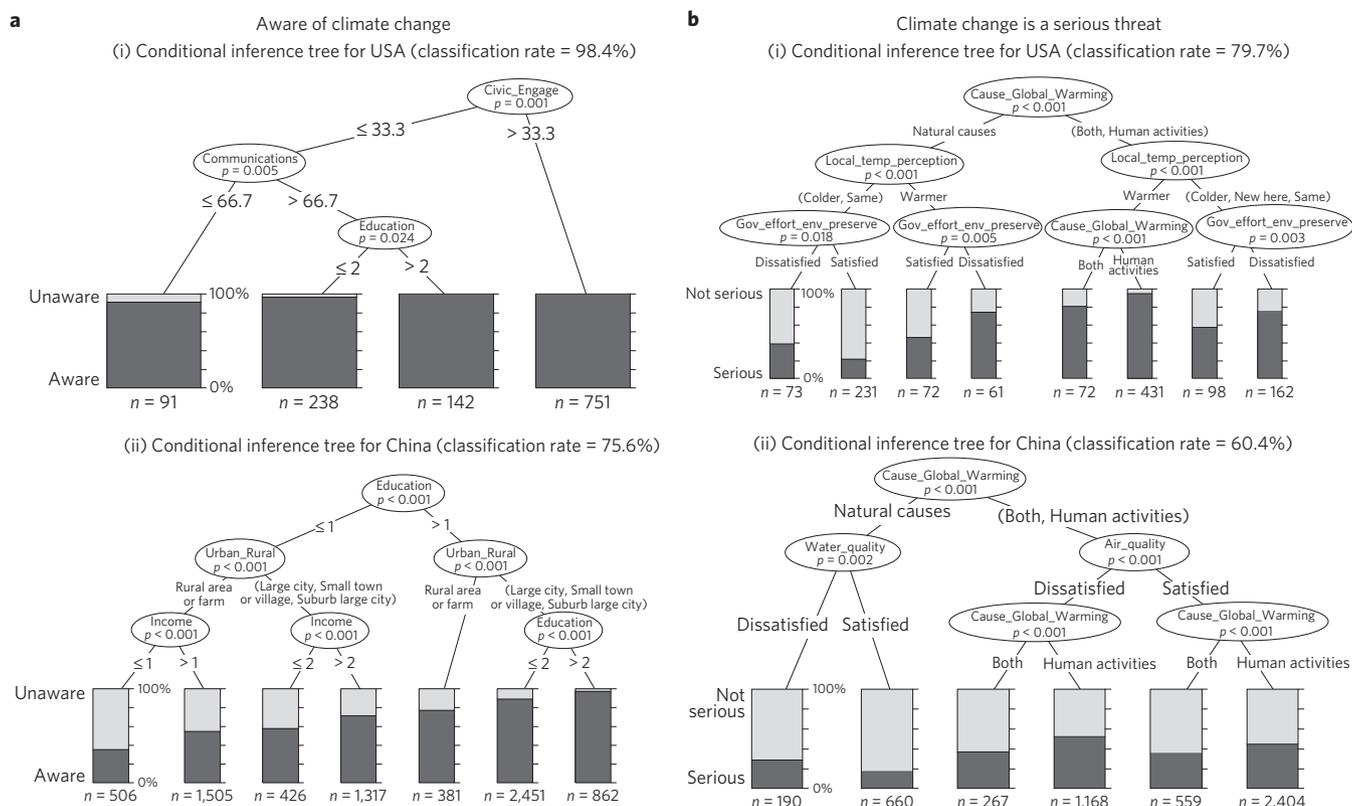
Figure 2 | Classification tree models for predicting climate change perceptions. Conditional inference (CI) classification tree for predicting climate change awareness (**a**) and risk perception (**b**) for the USA (i) and China (ii). For clarity of interpretation, the three most important predictor variables, as obtained from random forests variable importance evaluation, are retained for CI tree modelling. Stacked bar plot at each terminal node indicates the percentage of individuals that are aware of (or concerned about) climate change (dark) or not (light). Each tree is three levels deep and shows only statistically significant variables. Total sample sizes for the USA and China for awareness and concern are $N = 1,222$ and 7,448, and $N = 1,200$ and 5,248, respectively. The classification accuracy for each conditional inference tree is also provided. For full details and results from other nations, refer to the Supplementary Appendices.

World Poll, incomplete cases (or missing data) can limit the final sample size and/or number of predictor variables required for conventional regressions. The consequences are the possible loss of power, biased inference, underestimation of variability and distorted associations between predictors, which may lead to inaccurate conclusions[29]. As such, we use non-parametric unbiased recursive partitioning methods (that is, conditional inference trees and corresponding random forests)[30], which are an effective way to overcome the limitations of conventional regression methods (for example, logistic regression; see Methods for details)[29]. In addition, random forests can achieve high predictive accuracy, and provide unbiased robust ranking of predictor importance (accounting for complex interactions between predictors and unbalanced response classes), all while using as much data as possible[31].

Predictors of climate change opinions vary worldwide

Across nations, the ensemble random forest models are highly accurate (mean $81.5 \pm$ s.d. 7.5% for awareness and $84.3 \pm 8.6\%$ for risk perception) and perform well (area under ROC; 0.88 ± 0.04 for awareness and 0.92 ± 0.05 for risk perception; Supplementary Fig. 1). The resulting conditional inference (CI) tree models, one per nation, also have high classification accuracies (mean $75.6 \pm 11.5\%$ (awareness) and $81.8 \pm 11.7\%$ (risk perception)), particularly in North America and Western Europe (awareness), and in Latin America and the Caribbean (risk perception; Supplementary Fig. 2).

As an illustration, Fig. 2 presents the CI tree results for predicting the awareness and risk perception of climate change in the United States (USA) compared to China (results for other nations in Supplementary Appendices 1 and 2). In the USA, the most important predictors of climate change awareness are civic engagement, communication access and education. Residents with higher levels of civic engagement are almost always aware of climate change (rightmost node), whereas those with lower levels of civic engagement and communication access tend to be unaware (Fig. 2a(i)). In contrast, the key predictors of climate change awareness in China are education, geographic location (urban/rural) and household income. Lower-income residents who are poorly educated and living in a rural area or on a farm are the least aware (leftmost node), whereas those who are highly educated and urban are the most aware of climate change (Fig. 2a(ii)).

In the USA, the strongest predictors of climate change risk perceptions are beliefs about the cause of climate change, perceptions of local temperature changes, and attitudes towards government efforts for national environmental preservation. Americans who believe that climate change is human-caused and that average local temperatures are getting warmer perceive climate change as a greater risk (third rightmost node). Americans who think that climate change is natural, that average local temperatures are becoming colder or staying the same, and who are satisfied with environmental preservation efforts perceive climate change as a low or non-existent risk (Fig. 2b(i)). Other studies in the USA have found that growing partisan and ideological polarization within the American public over the past decade is also a key driver of public risk perceptions. American liberals and Democrats are more likely to express concern about climate change than are conservatives and Republicans[32,33]. Unfortunately, there is little cross-national data
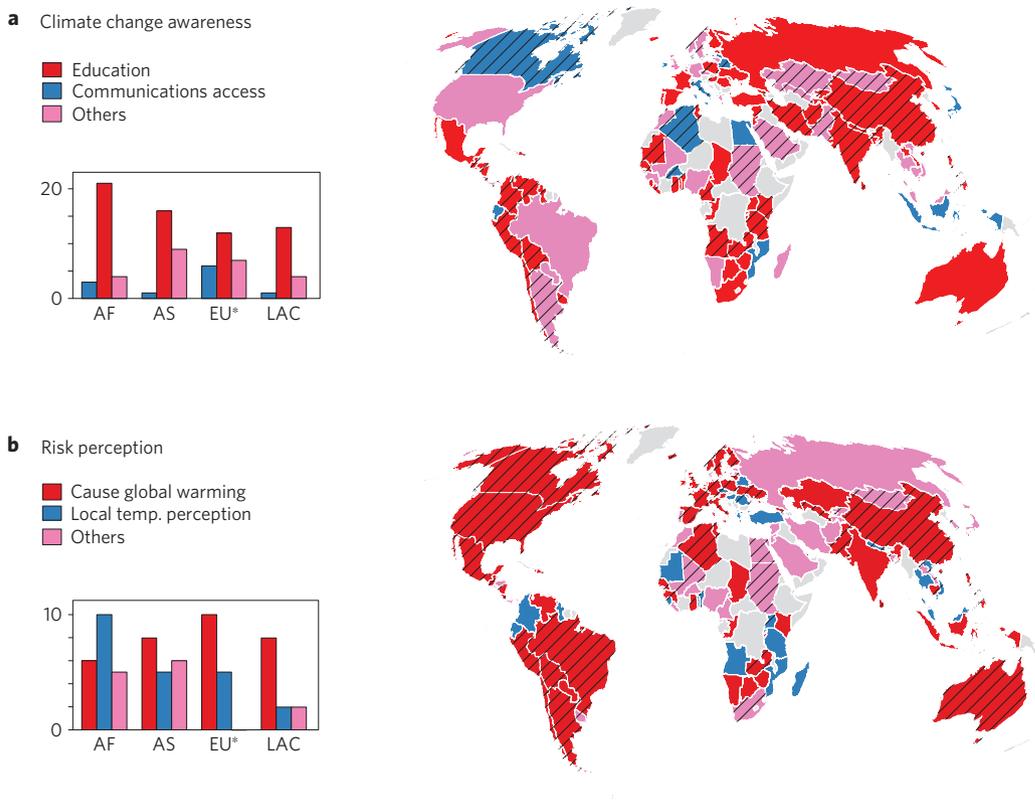
Figure 3 | Top-ranked predictors of climate change perceptions worldwide. Top-ranked predictor of climate change awareness (**a**) and risk perception (**b**). The maps show results from the random forest classification tree and variable importance evaluation for 119 nations. The three predictors with the highest frequencies are illustrated for a subset of nations, where the most frequent predictors are available for importance evaluation, across four geographic regions (bar plot insets; awareness $N = 97$ countries and risk $N = 67$; abbreviations in Fig. 4). The 'Others' category indicates all other predictors. Hashed lines indicate countries with a ratio of ≥ 1.5 (an arbitrary threshold) between top two predictors during the variable ranking evaluation. A larger ratio indicates the top-ranked predictor as more influential (see ratio classes in Supplementary Fig. 3). The three top-ranked predictors for each nation are available in Supplementary Figs 4–6 and Supplementary Dataset 1. AF, Africa; AS, Asia; EU*, Europe, North America and Australia; LAC, Latin America and Caribbean.

available on the role of political ideology for a global comparison[34], including this data set, so it is unclear whether liberal versus conservative ideologies are relevant predictors in most of the other countries of the world.

By comparison, this analysis finds that the strongest predictors of Chinese climate change risk perceptions are the belief that global warming is human-caused (similar to the USA) and dissatisfaction with local air quality (different than the USA; third rightmost node). Chinese who think that climate change is natural and are satisfied with water quality in their area (second leftmost node) perceive climate change as a low or non-existent risk (Fig. 2b(ii)). The correlation of perceived poor local air and water quality with climate change risk perceptions is probably due to widespread experience with poor air and water quality, particularly in the urban areas in China[35]. As found in other countries, many Chinese may be incorrectly applying a mental model of local pollution to the issue of climate change[36]. The role of intense local pollution in shaping the Chinese (and other) publics' understanding of and concern about climate change warrants further investigation. These results also indicate that the key predictors of climate change awareness and risk perceptions can be very different across countries.

Worldwide, education level (62% or 70 countries; $N = 113$ owing to missing data) and beliefs about the cause of climate change (48% or 57 countries; $N = 119$) were frequently the top-ranked predictors of climate change awareness and risk perceptions, respectively (in red; Fig. 3; also see Supplementary Figs 3–6). To assess the relative importance of the top predictor across the countries, we compute the ratio between the two top-ranked variables. We find

that over 60% ($N = 70$) and over 80% ($N = 57$) have education and beliefs about the cause of climate change, respectively, as very influential top-ranked predictors (ratio ≥ 1.5; larger ratio indicates more influence; Fig. 3 and Supplementary Fig. 3). The frequencies of the predictors across the regions were not significantly different (awareness: $\chi^2 = 9.52$, $p = 0.15$; risk: $\chi^2 = 11.0$, $p = 0.09$). Although this result supports our hypotheses[8,14,20], a significant proportion of nations had a different top-ranked predictor (Supplementary Fig. 4). For example, perception of local temperature change is the strongest predictor of risk perceptions in many Asian (for example, Nepal, Thailand and Vietnam) and African countries (for example, Madagascar, Mozambique and Rwanda). This finding is particularly important because previous research has found that many individuals around the world have accurately detected recent changes in local temperature anomalies[23], with research also suggesting that perceived local warming can influence risk perceptions[24,25]. Together, the results suggest that as societies become more educated (particularly in the developing world) and as more people begin to experience more pronounced and atypical changes in local weather patterns, awareness of climate change and perceptions of climate change as a serious threat are likely to increase worldwide. Thus, investing in primary and secondary education may be an effective tool to increase awareness and risk perceptions of climate change. In addition, the learning of new knowledge and skills to reduce vulnerabilities and manage climate change risks also has the benefit of helping to achieve global sustainable development goals[37,38]. It is important to note, however, that education can interact with political ideology in predicting risk
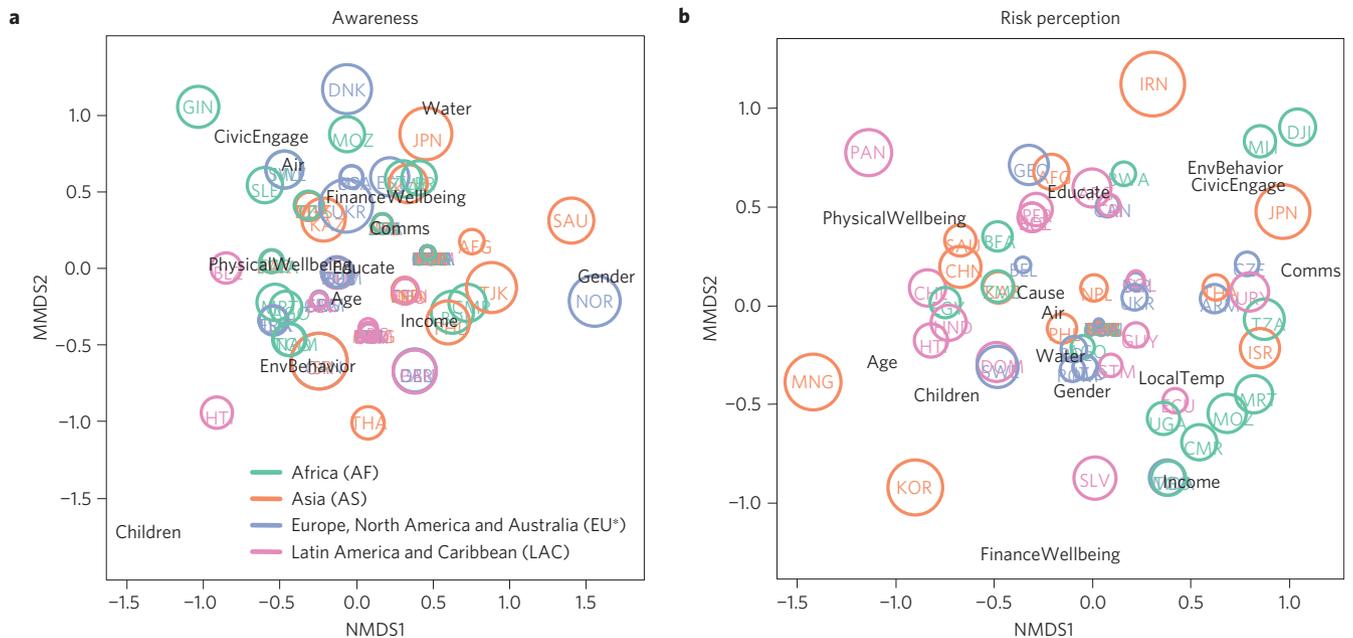
Figure 4 | Ordination of important predictors of climate change perceptions worldwide. Non-metric multidimensional scaling (NMDS) analysis of significant predictors of climate change awareness (**a**) and risk perception (**b**). We present an ordination or visual representation of pattern proximities that maximizes the sample size using data from 90 nations and 12 predictors for awareness, and 70 nations and 14 predictors for risk perception. Two-dimensional stress is 20.7 and 21.6 for awareness and risk, respectively. The non-metric fit (R-squared) between the ordination distances and original dissimilarities is 96% and 95% for awareness and risk perception, respectively. Nation and predictor ordination scores are plotted to illustrate their dissimilarities; countries are abbreviated in 3-letter code (see Supplementary Fig. 1). Bubble size for each country indicates the goodness of fit (between squared values and stress), where large values point to poor fit. Abbreviations in black are predictors of climate change perceptions. The distance of each predictor to a nation indicates its importance—the nearer, the more important. Another data matrix maximized the number of predictors, but both results share the broad overall trend (see Supplementary Fig. 7).

perceptions, as recent studies in the USA have demonstrated. In the USA, greater educational attainment is correlated with greater climate change risk perceptions among liberals and Democrats, but lower risk perceptions among conservatives and Republicans. In essence, greater educational attainment enables partisans to develop stronger arguments to support their ideological responses to the issue[33].

Nation indices poorly associate with predictors of opinions

Next, we investigated the grouping of key predictors of climate change awareness and risk perception across all countries (derived from the prior individual-level random forests analysis). We assessed whether these groupings are associated with each country's geographic region (for example, Africa versus Europe), level of national development, ecological indices, or vulnerability to climate-related hazards (Supplementary Figs 4–6 and Supplementary Datasets). That is, do nations that share the same key predictors of climate change awareness and risk perception also share similar national characteristics? The nation-level indices include the Human Development Index (HDI), GDP, carbon emissions per capita, globalization and governance[39,40], footprint of consumption and total biocapacity[41], exposure to sea-level rise, frequency of extreme weather events, and loss of agricultural productivity[42]. Owing to the relatively homogeneous (that is, culturally and economically) environment shared by nations belonging to a given region (for example, Europe versus Africa) as well as sub-region (for example, east Asia versus southeast Asia), we postulate that 'neighbouring' nations will tend to share more similarity with respect to key predictors of climate change awareness and risk perception compared to nations from other parts of the world. Consequently, such geographic association may be predicted by national development factors such as wealth or GDP, which also tend to cluster geographically.

Non-metric multidimensional scaling (NMDS) was performed to visually represent the country and predictor relationships as accurately as possible in a low-dimensional space[43]. The NMDS ordination and multivariate technique is necessary because of the multidimensional nature of our data, where up to 18 predictors are considered. The NMDS assesses the dissimilarity among countries in a common multi-predictor space using the distance matrix (that is, Bray–Curtis distance measure) and maps the observed inter-country dissimilarities nonlinearly onto two-dimensional space[44,45]. The closer two countries are in the ordination space, the more similar they are in terms of the significant predictors they share (up to three are identified using the random forests method)[45]. We then analyse how national characteristics relate to the dissimilarities among countries by implementing the permutational multivariate analysis of variances test (ANOVA; ref. 46; details in Methods).

For climate change awareness, an ordination of 90 countries (76% of 119 nations) finds that many nations overlap near the centre of the predictor space, indicating that these nations share common key predictors of climate change awareness. For instance, Sierra Leone (3-letter code: SLE) and Sweden (SWE) each have education and civic engagement as two of their three top predictors (the nearer, the more important the predictor is to the country) and hence are relatively close to each other in the top half of the ordination (Fig. 4a). The Latin American region is the most homogeneous (the nations in this region are more similar to each other than those in other regions) and is different from all other regions except Europe ($F = 5.3$, $p < 0.01$; Supplementary Table 1a). None of the national indicators is statistically significant in explaining the actual dissimilarity space (Supplementary Table 1a). Furthermore, national development and ecological indicators, but not the climate change vulnerability factors, correlate weakly (Mantel = 0.14, $p < 0.01$) with the key multi-predictor matrix.

Conversely, for climate change risk perception, many of the 70 nations (59% of 119 nations) are scattered across the ordination space of risk perception key predictors, indicating that many nations have a distinctive set of predictors (Fig. 4b). Nevertheless, some countries do share some predictors. For instance, both Afghanistan (AFG) and Peru (PER) have beliefs about the cause of climate change and education as two key predictors and are thus close together in the top half of the ordination (Fig. 4b). Not surprisingly, we show that broad geographic region (for example, Asia), as an indicator, poorly predicts how similar countries are in terms of their shared key predictors ($F = 0.99$, $p = 0.41$; Supplementary Table 1b). The sub-regional classification is the only significant indicator in explaining the multi-predictor pattern (Supplementary Table 1b); the national indicators are uncorrelated with the predictors matrix (Mantel < -0.01, $p > 0.57$). The results indicate some influence of geographic proximity on the predictors of risk perception. However, owing to limited sample sizes in relevant secondary data sets (for example, the World Values Survey)[14], the effects of cultural and economic proximities cannot be estimated. Overall, the results indicate that widely used national indicators of sustainability (for example, HDI and GDP) are poor predictors of the correlative structure of climate change awareness and risk perception globally, and therefore underscore the need to investigate other social and cultural measures.

Beyond the strategies of improving basic education, climate literacy, and public understanding of climate change[47], the results indicate that other factors also shape public responses. The observed heterogeneities in the key predictors of climate change risk perceptions across countries suggest that each country has its own relatively unique set of correlates. Therefore, national and regional programmes aiming to increase citizen engagement with climate change must be tailored to the unique context of each country, especially in the developing world. In addition, this study supports the growing call for cross-cultural research in anthropology, psychology, sociology, geography, and other fields on the issue of climate change to understand the underlying contextual or cultural factors that influence individual and group attitudinal and behavioural outcomes. Importantly, climate change risk communicators should develop strategies informed by the predictors of public climate change awareness and risk perception among their own target audience.

Methods

Methods and any associated references are available in the online version of the paper.

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Author contributions
T.M.L., E.M.M. and A.A.L. designed the research, T.M.L. conducted the analysis. T.M.L. wrote the initial draft with inputs from E.M.M., P.D.H., C.-Y.K. and A.A.L.

Additional information
Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to T.M.L. or A.A.L.

Competing financial interests
The authors declare no competing financial interests.

Methods

Data collection. This study uses data collected by the Gallup World Poll in 2007–2008 in 119 countries, representing over 90% of the world's adult population. Surveys were conducted with randomly selected nationally representative samples using either telephone or face-to-face interviews. The questions were translated into the major languages of each country. Telephone interviews were used in countries with more than 80% telephone coverage or where it is the traditional survey methodology. Survey sampling was representative of the national population aged 15 and older. The sampling frame includes all populated places within each country, both rural and urban, except inaccessible areas or where the safety of interviewers was threatened. In countries where face-to-face surveys were conducted, 100 to 135 ultimate clusters (sampling units) were selected, consisting of clusters of households. Sampling units were stratified by population size or geography and clustering was achieved through one or more stages of sampling. Where population information was available, sample selection was based on probabilities proportional to population size; otherwise simple random sampling was used. Samples were drawn independently of any samples drawn for surveys conducted in previous years. Within sampling units, random routes were used to sample households, with interviews attempted up to three times per household. Respondents were randomly selected within households using a Kish grid. In countries where telephone interviews were conducted, random-digit-dialling or a nationally representative list of phone numbers was used. In countries with high mobile phone use a dual mobile/landline sampling frame was used. To maximize the sample size of individuals and countries, we treated responses from countries collected in either 2007 ($N = 11$ countries), 2008 ($N = 46$) or both ($N = 62$) as representative of the same period (2007–2008). For an extensive treatment of the methodological approaches, see previous works using similar data[23,48] and the World Poll methodology[34,49] and (http://www.gallup.com/strategicconsulting/worldpoll.aspx). Surveyed countries included in our study are listed in Supplementary Fig. 1. Certain countries, namely Azerbaijan, Hong Kong (SAR, China), Iraq, Palestinian Territories and Taiwan, were excluded from our analyses owing to incomplete national development and vulnerability characteristic data. Countries were sampled from all first- and second-order macro-geographical regions excluding Oceania. See Supplementary Dataset 1 for more additional information.

Measures. Dependent measures. To measure climate change awareness, participants were asked, 'How much do you know about global warming or climate change?' Possible responses included: 'I have never heard of it', 'I know something about it', and 'I know a great deal about it'. A small number of participants refused to answer the question or else said 'Don't know'. The final measure is a binary variable that classifies an individual as being 'aware' ('I know something about it' or 'I know a great deal about it') or 'unaware' ('I have never heard of it' or 'Don't know'). Respondents who were 'aware' about climate change were then asked, 'How serious of a threat is global warming to you and your family?' Response categories included: 'Not at all serious', 'Not very serious', 'Somewhat serious', and 'Very serious'. We then created a binary risk perception variable grouping responses into either 'serious' ('Somewhat serious' or 'Very serious') or 'Not serious' ('Not at all serious' or 'Not very serious'). We treat our responses as binary so that they are consistent and comparable with previous studies, and we can detect clear differences between two response classes with sufficient sample size for each class. Admittedly, we may lose some data resolution, but it is beyond the scope of the paper to quantify the effect of collapsing the response classes.

Independent measures. We obtained data from a number of sources to examine individual-level and nation-level predictors of climate change awareness and risk perceptions. At the individual level, we used individual variables and composite indices from the Gallup World Poll data set. These included basic demographics (for example, gender, age), a communications index, several well-being measures, beliefs about climate change (for example, causes of global warming), and behaviours and opinions on related issues (for example, environmental behaviour). For global and cross-cultural compatibility, Gallup has developed several harmonized variables (for example, education) that are often unique to countries[34,49]. The independent measures include both nominal (including binary) and ordinal (including continuous) variables.

Individual level. The demographic variables include nation, gender (binary: male or female), age (15–99), marital status (nominal: divorced; domestic partner; married; separated; single/never been married; widowed), number of children under 15 years old (0–60), religion (nominal: Buddhist; Christian; Hinduism; Islam; others (29 in total)), education level (ordinal: elementary education or less (up to 8 years of basic education); secondary and tertiary (9–15 years of education); or four years of education beyond high school and/or received a 4-year college degree), household income within country quintiles (ordinal: Poorest 20% to Richest 20%), and the household location (nominal: rural area or farm, large city, small town or village, or suburb large city; 'urban/rural').

Gallup has constructed and validated several political, social and economic indices from individual items in the World Poll, including: Macroeconomics

(national economic well-being), Financial Wellbeing, Personal Health, Civic Engagement, and Communications. We briefly describe the indices specifically used in our study. Note that each index is calculated in a particular way that is elaborated in the methodology handbook[34]. The Communications Index ('Comms') assesses the degree to which respondents are connected via electronic communications (at least four items). For instance, the index scores are computed in the following way. For each individual record, the following procedure applies: the first two questions (landline telephone and cellular phone) are used to determine whether a respondent has a phone and is used to create the phone component of the index. If respondents answer 'yes' to either question, they are assigned a score of '1' for the phone component and a '0' if they do not have a phone. For the remaining two questions, positive answers are scored as a '1' and all other answers (including don't know and refused) are given a score of '0'. An individual record has an index calculated if it has valid scores for all three components. A record's final index score is the mean of items multiplied by 100 (that is, 0, 33.33, 66.67, or 100).

The Financial Wellbeing Index ('FinanceWellbeing') is a composite measure of respondents' personal economic situations and the economics of the community where they live (at least four of five items). The Physical Wellbeing Index ('PhysicalWellbeing') measures perceptions of one's own health (at least four of six items). The Civic Engagement Index ('CivicEngage') assesses how often respondents volunteer their time and assistance to others (at least two of three items). For this index, the following method applies: The three items are recoded so that positive answers are given a '1' and all other answers (including don't know and refused) a '0'. If a record has no answer for an item, then that item is not used in the calculations. An individual record has an index calculated if it has scores for at least two items (0 or 1). A record's final index score is the mean of valid items multiplied by 100 (that is, 0, 33.33, 66.67, or 100).

The beliefs, opinions and behaviour items used include quality of air in your area, quality of water in your area, nation's effort in preserving the environment (binary: satisfied or dissatisfied), an environmental behaviour index comprised of four behaviours: 'Active in environmental group'; 'Voluntarily recycled'; 'Avoided certain products' and 'Tried to use less water', cause of global warming (nominal: human activities, natural causes, or both), and local temperature change perception (nominal: nominal; warmer, colder, same, or new here). The latter two items are included only for the risk perception analyses.

A detailed description of the questions and Gallup indices used for this study is in Supplementary Dataset 2. For more details on the sampling and data collection methodology, post-data weighting and Gallup indices, see the Gallup World Poll research methodology and codebook[34].

National level. At the national level, we focused on a handful of development, ecological and vulnerability measures for which data was available for all 119 countries in the data set. These include the Human Development Index (http://hdr.undp.org/en/statistics/hdi), carbon dioxide emissions in metric tons per capita (in 2007), GDP per capita in USD (in 2007; http://data.worldbank.org/indicator), globalization (a measure of the economic, social and/or political aspects of globalization)[40], and an aggregated Worldwide Governance Indicator (a principal component derived from six dimensions of governance: Voice and Accountability; Political Stability and Absence of Violence/Terrorism; Government Effectiveness; Regulatory Quality; Rule of Law; and Control of Corruption[39]).

The ecological measures include the ecological footprint of consumption and the total biocapacity in global hectares per capita obtained from the Global Footprint Network[50] (http://www.footprintnetwork.org/en/index.php/GFN/page/methodology), which have been used in recent environmental sociology studies[51,52]. The national footprint of consumption, the demand on nature, utilizes yields of primary products (from cropland, grazing, forest, fishing ground, carbon, and built-up land) to calculate the area necessary to support a given activity in a nation, taking into account imports and exports. The total biocapacity, the capacity to meet the demand, is quantified by calculating the amount of biologically productive land and sea area available to provide the resources the nation consumes and to absorb its wastes, given present technology and management practices[41].

Extreme weather events, sea-level rise and storm surge and loss of agricultural productivity were included as climate change vulnerability measures. Although there are many vulnerability measures available, most are regarded as conceptually, methodologically and empirically limited[53]. For our study, we adopted a recently developed set of three indicators that represents the projected near-term risk exposure (2008–2015; ref. 54) that are more appropriate and reasonable. These indices incorporate climate drivers, resilience factors, and concerns related to project economics, potentially providing cost-effective allocation of adaptation assistance[42]. The formula used in our study accounts for not only potential climate change impacts and differential country vulnerability, which is affected by both economic development and governance, but also is adjusted for donor concerns related to project economics (that is, the international differences in project unit costs and probabilities of project success)[42].

Unless indicated, all data are averaged between 2007 and 2008. All indicators were log-10 transformed before data analysis to reduce effects of outliers.

Statistical analysis. Recursive partitioning methods. We evaluate the influence of predictor variables on climate change awareness and risk perception using non-parametric recursive partitioning methods. We explore and analyse our data using unbiased recursive partitioning (adopted from machine learning) by classification conditional inference trees and corresponding random forests[55]. A random forest is essentially a set or ensemble of classification or regression trees, where each tree is constructed based on the principle of recursive partitioning (that is, feature space is recursively divided into regions comprising observations with similar response values)[56]. Random forests can essentially handle large numbers of predictor variables (that is, small n large p cases; high-dimensional data), even in the presence of complex interactions (even high-order ones), and have been used in many different scientific fields ranging from bioinformatics and remote sensing, to psychological research[30]. For an instance of complex interaction, see the results from China, where we identified an asymmetric interaction between income and education (left branch) as well as a nonlinear effect with education (right branch), typically not captured using standard regression models (Fig. 2a(ii)).

Random forests have repeatedly shown to achieve high predictive accuracy (relative to more traditional regression methods). They also provide robust ranking of variable importance (via the conditional permutation method), measuring the impact of each predictor variable individually, as well as in multivariate interactions with other variables, even among highly correlated predictors, on predictive accuracies[31]. However, the robust permutation scheme reflecting the true impact of each predictor variable requires complete cases. Thus, given the prevalence of incomplete cases (that is, missing data) in some of data, we minimized spurious correlations by testing for collinearity among our non-nominal predictors (that is, 'Education', 'Age', 'CivicEngage', 'Comms', 'FinanceWellbeing', 'PhysicalWellbeing', and 'EnvBehavior'). On the basis of our correlation results, we did not find our ordinal and continuous variables to be highly collinear across all nations (awareness: Spearman ≤ 0.58; risk reception: Spearman ≤ 0.57).

One other advantage of using random forest, as opposed to more classical regression methods, is that we can use as much data as possible. In high-dimensional stratified data such as this study, incomplete cases and/or variables are common with the final sample size and/or predictor variables being drastically reduced. Simulations and data imputation methods repeatedly showed that missing data can lead to a loss of power, biased inference, underestimation of variability and distorted associations between predictors[29]. However, the random forests may adequately overcome this bias by having surrogates, as recently shown in ref. 29. As described in ref. 18, the random forest handles missing values by surrogate splits which attempt to mimic the primary split (obtained by the best split using only non-missing data) of a node. Surrogate splits are supposed to resemble primary split as accurately as possible, producing the same decisions. For a very detailed review of recursive partitioning and random forests, and its advantages over classical regression methods such as linear and logistic regressions, see ref. 30.

More specifically, we use the conditional inference trees and random forests to examine the correlative structure of climate change perceptions at the national level. Conditional inference trees embed tree-structured regression models into a well-defined theory of conditional inference procedures. This technique is suitable for non-parametric data (for example, nominal and binary) and basically all measurement scales of covariates (including nominal variables with many levels; for example, 'Religion' and Nation in this study). Breiman's random forest approach is implemented in the below-stated statistical package[57]. The use of the unbiased classification tree algorithm uses p values for variable selection (permutation-based significance tests) and as a stopping criterion, and hence is independent of pruning and overfitting[30].

In essence, we use conditional trees and random forests rather than a conventional logistic regression modelling approach mainly because it readily accounts for possible interactions and handles non-parametric responses; there is no need to consider data imputation techniques; and the models generate high prediction accuracies. With our approach, we can identify the most important individual-level predictors for any given country, using as many data and predictors as possible, as missing data is not an issue. In summary, our approach is robust (that is, less data assumptions), allows us to look at a lot more variables (including those with numerous categorical levels) and responses (and their high-level interactions), and pick out the most important ones, minimizing bias related to missing data deletion and/or imputation methods.

We used the R package party for our recursive partitioning analysis. Whereas the random forest method used all available predictors (function *cforest*), only up to three most important variables are used in the single tree growing process (function *ctree*). For our national analysis, our random forest generated 1,000 trees per nation. The prediction accuracy for each tree was calculated using an honest or 'out-of-bag' built-in test sample, making it unnecessary to create training and testing samples[30]. We followed recommendations on the maximum number of surrogates and number of randomly pre-selected variables[29,31]. We assessed the predictive performance of our random forest model in accurately classifying the data using the threshold-independent area under the Receiver Operating Characteristic (ROC) curve (AUC), where the closer the AUC is to unity the more accurate the model. We used the unbiased permutational variable importance

measure (function *varimpAUC*), particularly suited for unbalanced response classes in our study, to screen for the most influential variables[58], which are subsequently used to build a single conditional inference tree for visualization and interpretation (up to three per nation) as well as for our multivariate analysis across nations (see below). A predictor is considered significant if its absolute value is larger than that of the lowest ranked predictor. This means that it is possible to have between zero and maximum number of variables that are significant and that we generate a set of key correlates of national climate change perceptions. To assess the relative importance of the top predictor across the countries, we also compute the ratio between the two top-ranked variables. The larger the ratio, the more influential the top-ranked predictor is in the classification tree.

Multivariate statistics. Non-metric multidimensional scaling. We perform non-metric multidimensional scaling (NMDS; ref. 43), an unconstrained ordination method commonly used in environmental or ecological research, to evaluate the dissimilarity (or similarity) among countries in common multi-predictor space[59]. The distance matrix consisted of a set of common predictors shared by a subset of the countries. Only the top predictors (up to three) from each country, as screened from the unbiased variable importance method, were indicated as important, whereas the other predictors were not. We only use up to three important predictors because only the top predictors are the most influential, and some nations have only one or two top predictors. The main reason for using dichotomous important–not important data is that it is difficult to compare the arbitrary importance values across data sets from different countries. The distance matrix is calculated using the Bray–Curtis distance measure, which is most appropriate for incidence data[60]. The Bray–Curtis dissimilarity (D) for a pair of nations is as follows:

$$D_{ij} = 1 - \frac{2a_{ij}}{b_i + c_j}$$

where a_{ij} represents the total number of influential predictors common to both nations; b_i represents the number of influential predictors present only in nation i; and c_j represents the number of influential predictors present only in nation j. The Bray–Curtis dissimilarity is between 0 and 1, where 0 means the two nations have the same set of influential predictors (that is, they share all the influential predictors), and 1 means the two nations do not share any influential predictor.

NMDS maps observed 'community' dissimilarities nonlinearly onto two-dimensional ordination space with the ability to manage nonlinear predictor responses of any shape[44]. The stress or goodness of fit evaluates the nonlinear monotone association between ordination distances and global dissimilarities. The closer two nations are in the ordination space, the more similar they are in terms of the significant predictors they share[45]. For the implementation of NMDS, we used function *metaMDS* from the R library VEGAN.

We carried out NMDS on two sets of multi-predictor distance matrices to evaluate the effects of number of samples (or countries) and number of predictors. For the first data set, we select to maximize the number of samples through the exclusion of a handful of predictor variables (that is, government preservation effort, marital status, religion and urban/rural) that are missing in several countries (awareness: $N = 90$, risk perception: $N = 70$). Alternatively, we choose to maximize the range of key predictors across countries. We remove countries that do not have the full set of predictor variables, which leads to a much lower sample size of nations (awareness: $N = 81$, risk perception: $N = 64$). We also tested if there are significant differences in group homogeneities among geographic regions using function *betadisper* and permutation tests, as well as Tukey HSD test for pairwise differences between groups.

Multivariate ANOVA based on dissimilarities. Further, we analyse the key predictor–national characteristics relationships in full space. We implement the permutational multivariate analysis of variances using distance matrices calling the *adonis* function (handles both continuous and factor predictors) and available in VEGAN library[44]. We included all eleven national factors in this analysis (including a sub-regional classification of the nations). This approach partitioned the dissimilarities for the sources of variation, and used permutation tests (9,999 iterations) to examine the significance of those partitions[46,61]. We excluded only a nation with no screened key predictors in each analysis. We performed the *Mantel* test (9,999 permutations) to evaluate how well the predictor and national characteristic dissimilarity matrices correlate, as many of the indicators are highly correlated[62].

All analyses were carried out using R version 2.15.2 (ref. 63). Maps are produced using ESRI ArcMap version 10.

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