ELSEVIER

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha





Global rainbow distribution under current and future climates

Kimberly M. Carlson ^{a,b,*}, Camilo Mora ^c, Jinwen Xu ^{c,d}, Renee O. Setter ^c, Michelle Harangody ^c, Erik C. Franklin ^{c,e}, Michael B. Kantar ^f, Matthew Lucas ^c, Zachary M. Menzo ^g, Daniele Spirandelli ^h, David Schanzenbach ⁱ, C. Courtlandt Warr ^j, Amanda E. Wong ^{k,l}, Steven Businger ^g

- ^a Department of Environmental Studies, New York University, New York, NY 10003, USA
- ^b Department of Natural Resources and Environmental Management, University of Hawai'i at Mānoa, Honolulu, HI 96822, USA
- ^c Department of Geography and Environment, University of Hawai'i at Mānoa, Honolulu, HI 96822, USA
- ^d School of Geosciences, University of South Florida, Tampa, FL 33620, USA
- e Hawai'i Institute of Marine Biology, School of Ocean and Earth Science and Technology, University of Hawai'i at Mānoa, Kāne'ohe, HI 96744, USA
- f Department of Tropical Plants and Soil Sciences, University of Hawaiʻi at Mānoa, Honolulu, HI 96822, USA
- g Department of Atmospheric Sciences, University of Hawaiʻi at Mānoa, Honolulu, HI, USA
- ^h Haley & Aldrich, Inc., 6420 S Macadam Avenue Suite 100, Portland, OR 97239, USA
- ⁱ Information Technology Services, University of Hawaiʻi System, Honolulu, HI 96822, USA
- j Independent, Kailua-Kona, HI 96740, USA
- k Department of Oceanography, University of Hawaiʻi at Mānoa, Honolulu, HI 96822, USA
- ¹ Department of Plant Sciences, University of California, Davis, Davis, CA 95616, USA

ARTICLE INFO

Keywords: Cultural ecosystem services Relational value Climate change Atmospheric optical phenomena Future global scenarios

ABSTRACT

Rainbows contribute to human wellbeing by providing an inspiring connection to nature. Because the rainbow is an atmospheric optical phenomenon that results from the refraction of sunlight by rainwater droplets, changes in precipitation and cloud cover due to anthropogenic climate forcing will alter rainbow distribution. Yet, we lack a basic understanding of the current spatial distribution of rainbows and how climate change might alter this pattern. To assess how climate change might affect rainbow viewing opportunities, we developed a global database of crowd-sourced photographed rainbows, trained an empirical model of rainbow occurrence, and applied this model to present-day climate and three future climate scenarios. Results suggest that the average terrestrial location on Earth currently has 117 ± 71 days per year with conditions suitable for rainbows. By 2100, climate change is likely to generate a 4.0–4.9 % net increase in mean global annual rainbow-days (i.e., days with at least one rainbow), with the greatest change under the highest emission scenario. Around 21-34 % of land areas will lose rainbow-days and 66-79 % will gain rainbow-days, with rainbow gain hotspots mainly in high-latitude and high-elevation regions with smaller human populations. Our research demonstrates that alterations to non-tangible environmental attributes due to climate change could be significant and are worthy of consideration and mitigation.

1. Introduction

Atmospheric optical phenomena such as rainbows, mirages, and coronas result from the interaction of light and matter in the atmosphere (Gedzelman and Vollmer, 2008) and are thus part of the physical environment of Earth's ecosystems. Anthropogenic climate change has substantial effects on atmospheric optical phenomena. For instance, climate change is linked to increasing severity and frequency of forest

fires which boost particulate matter concentrations and change sunset quality (Haider et al., 2019; Hyslop, 2009). Yet, most climate change impact research has centered on changes with clear socio-economic links like heat waves, droughts, wildfires, storms, floods, and sea level rise (Adger et al., 2013; Mora et al., 2018). We largely lack an understanding of how anthropogenic climate change alters the location and timing of atmospheric optical phenomena.

The rainbow, a common atmospheric optical phenomenon, is a

^{*} Corresponding author at: 285 Mercer Street, 8th Floor, New York, NY 10003, USA. *E-mail address:* kimcarlson@gmail.com (K.M. Carlson).

multicolored circle in the sky that results from the refraction and reflection of light by liquid water drops (Hardwick, 2004). Primary rainbows are only visible from ground level at sun angles between 0° and 42°, which occur in the early morning and late afternoon (Fig. 1) (Businger, 2021). Rainbow sightings are further constrained by the presence of rain and absence of cloud cover, which may block sunlight. Climate change will thus alter the spatio-temporal distribution of rainbow occurrence by affecting evaporation and convergence of moisture which alter patterns of precipitation (Pendergrass and Hartmann, 2014; Zhang et al., 2013) and cloud cover (Boucher et al., 2013; Enriquez-Alonso et al., 2016). For instance, more extreme rainfall concentrated in brief periods occurring during fewer days per year could lower rainbow occurrence by increasing the number of annual dry days, reducing rainfall during times of day with suitable sun angles, and blocking sunlight with cloud cover during rainy periods. Areas where precipitation changes from snow to rain under a warming climate may experience conditions more conducive to rainbow occurrence.

Rainbows have been part of the lived human experience throughout history and around the world and can also be found in arts, literature, music, films, folklore, religion, and mythology (Hardwick, 2004; Lee and Fraser, 2001; MacCannell, 2018; Vince, 2020). The place-based nature of rainbows, their aesthetic qualities, and their various symbolic meanings may invoke emotion, support connections with cultural identity, and provide information about the natural world (Box 1). They are accessible in that they may occur in any environment, from cities to wilderness areas. Yet, to our knowledge, there has been no research exploring rainbows within the environmental values literature, despite

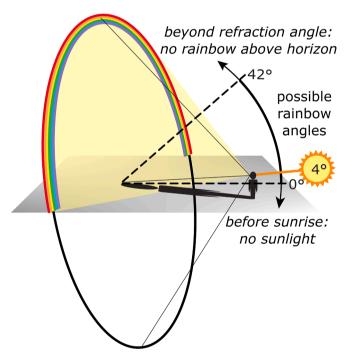


Fig. 1. Theoretical requirements for rainbow occurrence. From ground level, primary rainbows are only visible during the day, when sun angles are below 42° and direct sunlight - not blocked by clouds - can be refracted from a droplet of water (rain). Sun angle determines rainbow height in the sky. At sun angles $>42^{\circ}$, light refraction is below the horizon, so rainbows are not visible from ground level. For example, a rainbow can be viewed when the sun is behind the viewer with a solar angle of 4° , but not when the sun is directly overhead (90°), before sunrise ($<0^{\circ}$), or when the sun is in front of the viewer. These requirements restrict the timeframe and specific conditions of rain and cloud cover relative to the viewer needed for rainbows to occur. Thus, rainbows can be affected by anthropogenic changes in precipitation and cloud cover, including those due to increasing concentrations of greenhouse gasses in the atmosphere because of human activity.

its strong engagement with place and exploration of the linkages between experience of nature and human wellbeing (e.g., Chan et al., 2016; Chapin and Knapp, 2015; Russell et al., 2013).

Here, we situate rainbows within the ecosystem service cascade (Haines-Young and Potschin, 2010). First, we argue that rainbows are a geophysical *function* of ecosystems generated by the *process* of light refraction by rain droplets. Rainbows then provide cultural ecosystem services (Box 1), "the nonmaterial *benefits* people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experiences" (Millennium Ecosystem Assessment, 2005). While rainbows occur anywhere with appropriate sun angle, precipitation, and light, each viewer experiences a unique sensory encounter with each rainbow. Thus, the *value* of rainbows to people is derived partly from singular rainbow viewing experiences, events imbued with meaning based on the relationship between the viewer, the rainbow, and the surrounding context (e.g., place and time).

Conceptually, we argue that these values fall mainly into the relational category (Chan et al., 2016). Specifically, we observe that rainbows are experienced in specific places, are often connected with spirituality, beauty, and heritage, and are sometimes associated with experiences that contribute to a good life. They are also non-substitutable, in that replacements for the viewing experience such as a picture of a rainbow taken at that place or a rainbow in a different place would likely not offer equivalent value, especially when an individual often sees a rainbow in a particular location. These are all attributes of relational values as described by Himes and Muraca (2018). Rainbows may also have instrumental value; for instance, their occurrence could generate revenue via tourism.

Like other cultural ecosystem services (Satz et al., 2013), those generated by rainbows may have been overlooked by environmental researchers because of difficulties – real or perceived – in measuring and comparing the values they provide and the view that given other grave environmental problems facing humanity, a focus on rainbows is not high priority. Aesthetic cultural ecosystem services, while significant for human wellbeing and ecosystem management and conservation, have received particularly limited attention (Dronova, 2019; Tribot et al., 2018). Yet, like other functions that provide cultural ecosystem services (Adger et al., 2013), if rainbow frequency or distribution change due to shifts in climate, the value of rainbows in bridging human and nonhuman nature may also change. Research focused on these changing connections supports goals of equity and justice by recognizing diverse local values and norms that extend beyond those heavily influenced by Western European and colonial scientific traditions (Gould et al., 2020).

The effects of climate change on rainbow sightings, and associated implications for connections between people and places where rainbows occur, have been unknown. To evaluate how climate change may alter rainbow viewing opportunities, we ask: Under what conditions do rainbows occur? What is their current spatial distribution? How might climate change alter opportunities to view rainbows?

Our research informs whether and how rainbow occurrence is likely to change with changing climate across global locations and provides information about the regions where rainbows - and any contributions they make to human wellbeing - may incur the most significant changes. Our results can guide future analyses connecting such changes to the value rainbows provide to humans, to enhance understanding of how current planetary shifts are manifesting in personal and, by extension, cultural ways (Anderson, 2020).

2. Materials and methods

To address these questions, we first collected geographically and temporally located rainbow occurrence data and combined this with a dataset of presumed non-rainbows. We then used these data to train and validate a model of rainbow presence based on climate and sun angle data. Then, we applied this model to map current and potential future annual rainbow occurrence across the Earth's surface. Next, we

Box 1. Significance of rainbows to humans.

The rainbow is beautiful and ephemeral, a spectrum of color visible only while conditions of light and rain droplets are just right. Many have ascribed rainbows with positive meaning. For ancient Greeks, Romans, Norsemen, and Polynesians, rainbows were a path between Earth and Heaven created by Gods (Lee and Fraser, 2001; Businger, 2021). In the Bible, rainbows are mentioned as God's promise to never again flood the Earth (Kuruppu and Liverman, 2011). Contemporary society commonly uses rainbows in flags and emblems to symbolize peace, happiness, and equality (Vince, 2020). For instance, the University of Hawai'i adopted the rainbow as its mascot after a rainbow appeared during a football game when the Hawai'i team won (Associated Press, 2013). Rainbows are an object of fantasy in advertising and storytelling and a sign of hope, solidarity, and wellbeing (Lee and Fraser, 2001; Vince, 2020). Who has not heard that there is treasure at the end of the rainbow?

Rainbows have also been characterized in negative ways. In the folklore of the Karen people of Southeast Asia, the rainbow is a dangerous demon that eats children (Jenkins, 2019). In several cultures in Central and South America, it is a malign spirit that causes harm (Lee and Fraser, 2001). People from various tropical locales see rainbows as snakes (Löwenstein, 1961; Veland et al., 2013). For example, the Rainbow Serpent is a powerful and essential part of Aboriginal mythology across cultural groups on the Australian continent (Lee and Fraser, 2001).

Because of their association with light and rainfall, rainbows also provide information and meaning related to weather patterns. Rainbows have been attributed the ability to stop or start a rain shower. For example, in Estonian folklore, the rainbow provides rain by sucking up water from waterbodies and then sprinkling it back on Earth (Lee and Fraser, 2001). More functionally, rainbows are a near-term predictor of weather, as indicated by the phrase from American folklore "Rainbow in the morning, sailors take warning; rainbow at night, sailors' delight." (White and Hand, 2013). Here, the rainbow provides a gauge for the location and direction of a rain shower relative to the location of an observer.

quantified future potential changes in rainbow occurrence under several climate change scenarios and compared the distributions of projected human population to the locations of projected rainbow frequency. Finally, we identified hotspots of rainbow loss and gain under projected climate change.

2.1. Rainbow observations

We downloaded all photographs from Flickr (https://www.flickr.com) with the term "rainbow" in the hashtag, description, or title that were taken between 2004 and 2019 and that included date and time of photo collection and geographic location of photo upload. This resulted in 121,558 photographs. We then cleaned the dataset to ensure that photographs were unmodified precipitation-associated rainbows accurately located in time and space. First, we removed photographs taken prior to the launch of the Flickr platform (February 10, 2004). We also excluded photographs that were uploaded on a different date than the photo was taken, as this difference in time may indicate a change in location. Only photographs containing Exchangeable image file format (Exif) information, which includes precise time, date, and location

labels, were retained.

Co-authors of this manuscript manually curated the remaining photographs by viewing each photo and marking it as a rainbow or not. Specifically, curators eliminated photographs of rainbows that were not associated with precipitation (e.g., some images were of rainbow trout, flags, or children's drawings), and those with watermarks that potentially indicate photo modification and a time and location label not reflective of the time and location the photo was collected. Because manual photo review may lead to errors, photographs were curated a second time by randomly assigned co-authors.

After curation, we excluded rainbow observations with sun angles < 0° or > 42° that we calculated for each time and location (Section 2.3) because such angles may indicate a photo upload location different from the location the photo was collected. We acknowledge that this may have eliminated photographs taken by observers in aircraft or on slopes, which allow viewing of rainbows at such sun angles. The final rainbow dataset, which included observations on all continents except Antarctica, consisted of 7,094 photographs of atmospheric rainbows collected between February 11, 2004, and December 7, 2013 (Fig. 2).

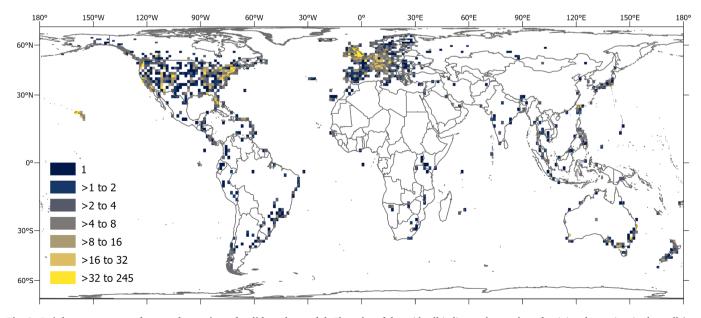


Fig. 2. Rainbow occurrence data used to train and validate the model. The color of the grid cell indicates the number of training data points in that cell (n = 7,094 positive rainbow observations).

2.2. Non-rainbows

The rainbow classification model (see Section 2.4) required information on conditions without rainbows. To provide these, we created a complementary dataset representing the same places where rainbow photographs were taken, but during random times from the period covered by the rainbow observation dataset. Because we assumed that non-rainbows were more common than rainbows, we selected three non-rainbow observations for each rainbow observation, generating a non-rainbow dataset with 21,282 records.

2.3. Predictor variables

Our predictive model assumes that rainbow occurrence is a function of rain droplets and light, which is an interaction between cloud cover and sun angle. Elevation gradients (e.g., hills) may also affect rainbow occurrence as they can influence the angle at which the sunlight can be refracted and reflected by raindrops back to the observer.

We derived mean total liquid phase precipitation rate (kg m^{-2} s⁻¹), cloud cover (%), elevation (m), and sun angle (°) for each observation in the rainbow and non-rainbow datasets (Dataset 1). We used ERA5 hourly data on single levels for precipitation and cloud cover (Hersbach et al., 2018). ERA5 is an atmospheric reanalysis of past climate with 0.25° resolution. We chose ERA5 data because of their global scope, time frame that covered our photo data, hourly temporal resolution, and broad use among global change researchers. Because ERA5 mean total precipitation rate includes both liquid and solid phases (Hersbach et al., 2018), but rainbows should occur only in the presence of liquid phase precipitation which allows for refraction of light, we subtracted mean snowfall rate (solid-phase precipitation; kg m⁻² s⁻¹) from mean total precipitation rate (kg m⁻² s⁻¹). When liquid precipitation values were less than zero, a known effect of spatial interpolation of the ERA5 precipitation data (European Centre for Medium-Range Weather Forecasts, 2013), we set these values to zero. To ensure that training data were comparable to the three-hour projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016; see Section 2.5), we averaged climate variables over three-hour periods, including the hour before and the hour after the observation time. Sun angles were calculated for each time and location using the R packages insol (Corripio, 2020) and suncalc (Thieurmel and Elmarhraoui, 2019). Elevation was extracted from NASA Shuttle Radar Topography Mission global 1 arc second data (USGS, n.d.).

2.4. Model training and validation

We trained and tested a recursive partitioning and regression tree model to identify the conditions associated with rainbow occurrence. We used the *rpart* package in R to develop this model, using the "class" method with priors proportional to data counts (Therneau et al., 2022). To avoid overfitting, we pruned the model with a complexity parameter value of 0.3. To assess model utility, 70 % of rainbow and non-rainbow observations were used to train the model, and the remaining 30 % were used to evaluate model accuracy. We used overall accuracy and rainbow prediction accuracy to assess model quality. Including elevation and variation in elevation in initial model testing led to negligible improvements in accuracy, so we excluded this variable from the model. Thus, in the final model, the occurrence of a rainbow was the dependent variable, and sun angle, liquid precipitation, and cloud cover were independent variables.

2.5. Projected occurrence of rainbow conditions

To map changes in the distribution of the number of rainbow-days per year (i.e., the number of days per year with at least one rainbow), we applied the model to gridded global circa-2000 climate data and future circa-2100 climate projections. Specifically, we used ERA5 data

from 1996 to 2005, as well as three-hour data from 13 Earth System Models (r1i1f1p1 variant) under four scenarios developed for CMIP6 (Eyring et al., 2016). These consisted of the "historical" experiment in the period from 1996 to 2005, and the shared socio-economic pathways (SSPs) SSP1-2.6, SSP2-4.5, and SSP5-8.5 for the period from 2091 to 2100 (Table 1). We aggregated CMIP6 data into circa-2000 (1996–2005) and circa-2100 (2091–2100) decades for comparison. CMIP6 data consisted of three-hour liquid phase precipitation flux (i.e., precipitation flux minus snowfall flux) and cloud area fraction converted to percent cloud cover to match the ERA5 metric. Sun angles were calculated for the middle hour of each three-hour time chunk.

We applied the classification model to ERA5 data and the data from each Earth System Model in its original resolution. After rainbows were classified, we counted the number of days each year that rainbows were predicted in each grid cell and calculated the mean number of annual rainbow-days per grid cell across each ten-year circa-2000 and circa-2100 period. The decadal projections of each model were then interpolated to a $1.5^{\circ} \times 1.5^{\circ}$ global grid using bilinear interpolation. These gridded decadal mean projections were used to estimate the CMIP6 multi-model mean and standard deviation.

Changes in rainbows were quantified as the difference in CMIP6 derived days with rainbows in the circa-2100 and circa-2000 decades. We report means and standard deviations of rainbow-days weighted by grid cell area at a 14 km resolution, the approximate resolution of the human population dataset at the equator (see Section 2.7). Because most of our training data were collected over land, and because population datasets are limited to land areas, we report results only for grid cells that overlap with land. Current and future rainbow maps are available in Dataset 2, and maps of changes are available in Dataset 3.

2.6. Accuracy and precision assessment and sensitivity analysis

Climate change projections are subject to several sources of uncertainty, including uncertainty associated with an Earth Systems Model's initial conditions, as well as emissions scenarios and model attributes such as resolution (Lehner et al., 2020). To better understand uncertainties arising from the Earth System Models, we quantified precision, the variability in rainbow predictions among Earth System Models, and accuracy, the extent to which models predict the meteorological conditions that support rainbow occurrence in the historical climate. To assess precision, we calculated the average change in rainbows among Earth System Models and their coefficient of variation. We defined areas of high uncertainty as locations where the multi-model standard deviation exceeded the multi-model mean, and repeated calculations after removing those cells (Dataset 4). To assess accuracy, we compared the predicted number of annual rainbow-days, as described above, using the

Table 1
Earth System Models used to support rainbow occurrence models. We selected Earth System Models that provided three-hour data for precipitation, snow, and cloud cover for each year between 1996 and 2005 (historical experiment) and between 2091 and 2100 for all the following shared socioeconomic pathways (SSPs): SSP1-2.6, SSP2-4.5, or SSP5-8.5.

Earth system model	Data reference
ACCESS-CM2	Dix (2019)
AWI-CM-1-1-MR	Semmler (2018)
BCC-CSM2-MR	Xin (2018)
CMCC-CM2-SR5	Lovato (2020)
CMCC-ESM2	Lovato et al. (2021)
EC-Earth3	EC-Earth Consortium (EC-Earth) (2019)
IPSL-CM6A-LR	Boucher (2018)
KACE-1-0-G	Byun et al. (2019)
MIROC6	Tatebe and Masahiro (2018)
MPI-ESM1-2-HR	Jungclaus (2019)
MPI-ESM1-2-LR	Wieners (2019)
MRI-ESM2-0	Yukimoto (2019)
NESM3	Cao (2019)

ERA5 reanalysis data and the multi-model CMIP6 Earth System Model mean for the decadal average of circa-2000 predictions.

2.7. Population analysis

To understand relationships between change in rainbow-days and future populations, which allows us to begin to evaluate how alterations in rainbows induced by climate change may affect people, we used gridded global human population data consistent with the socioeconomic pathways associated with our climate scenarios (Jones and O'Neill, 2016). We extracted population for each land location considered in the analysis, for each climate scenario.

2.8. Hotspot analysis

To identify locations of substantial change in the number of annual rainbow-days between circa-2000 and circa-2100, we used the *hotspots* package in R (Darrouzet-Nardi, 2018). This approach first calculates the robust root mean square (RRMS) of the data x, where n is the number of data points and i represents each individual data point (Equation (1)).

$$RRMS = \sqrt{median(x)^{2} + \left(\frac{\sum |x_{i} - mean(x)|}{n}\right)^{2}}$$
 (1)

The hotspot cutoff is calculated as described in Equation (2), where p = 0.90 and F^{-1} is the inverse cumulative distribution function for the t distribution

$$cutoff = \left[median(\frac{x}{RRMS}) + F^{-1}(p) \right] \times RRMS$$
 (2)

3. Results

3.1. Rainbow prediction model

The rainbow prediction model had overall accuracy of 86 % and rainbow prediction accuracy of 75 %. The model parameters were as follows: 1) sun angle (no rainbow if <0.00096°); 2) precipitation (no rainbow if <1.15e-7 kg m $^{-2}$ s $^{-1}$); 3) sun angle (no rainbow if >41.33°); and 4) cloud cover (no rainbow if >96 %).

Fig. 3 depicts the bounds of the model, which largely conform to the theoretical expectations required for rainbow occurrence (Fig. 1)(Businger, 2021), overlaid on a density plot of rainbow observation points used for model training and testing. About 12 % of observations with very high cloud cover proportion and 12 % with very low precipitation were not captured by our model. Almost all observed sun angle values

(>99 %) were included by the model.

Results were qualitatively consistent among Earth System Models (Fig. 4a). The multi-model mean predicted the frequency of contemporary rainbows more realistically than any individual model (Fig. 4a). Overall, circa-2000 rainbow-days predicted from the CMIP6 multimodel mean and the ERA5 reanalysis database were highly correlated (Pearson's coefficient of correlation = 0.96; Fig. 4b). In locations with more than around 150 rainbow-days per year, CMIP6-derived rainbowdays were consistently less than ERA5-derived predictions, but predictions were still strongly and positively related (Fig. 4b). ERA5derived rainbow-days tended to exceed CMIP6-derived rainbow-days over much of the tropics and the Himalayas but were less than CMIP6 predictions in several other regions (Fig. 5c). Removal of grid cells with high uncertainty where the multi-model rainbow occurrence standard deviation exceeded the multi-model mean amplified the global gross mean change in rainbow-days in locations of loss or gain but maintained relative differences between the three future scenarios (Fig. 6a).

3.2. Current rainbow-days

Circa-2000, application of the rainbow prediction model to the ERA5 data suggests that the average global land location experienced 117 \pm 71 rainbow-days per year (mean \pm standard deviation of the mean), while the CMIP multi-model mean was 108 ± 57 rainbow-days per year. Across latitudes, areas closest to the poles had the fewest mean annual rainbow-days, while the tropics had the most annual mean rainbowdays. Examining frequency across regions, rainbows were very common in the coastal tropics, including parts of eastern South America (e. g., Suriname, Guyana), eastern Central America (e.g., eastern Nicaragua and Honduras), southern West Africa (e.g., southern Liberia), eastern East Africa (e.g., Kenya), eastern Madagascar, and many islands and archipelagoes (e.g., the Caribbean, the Hawaiian islands; Fig. 5a-b). They were also very common in select non-coastal areas, including the Andes mountains in northern Peru and southern Ecuador, and the border between Gabon and Republic of the Congo. They were least common in Antarctica, Greenland, the Arabian Peninsula, the Sahara Desert, and northwest China (Fig. 5a-b).

3.3. Future rainbow-days

By 2100, changes in cloud cover and liquid precipitation due to increased greenhouse gas emissions are projected to lead to a net increase in mean global annual rainbow-days, with a global annual mean of +4.3 (SSP 2.6) to +5.3 (SSP 8.5) additional rainbow-days across scenarios (Fig. 6b). After accounting for the projected future distribution

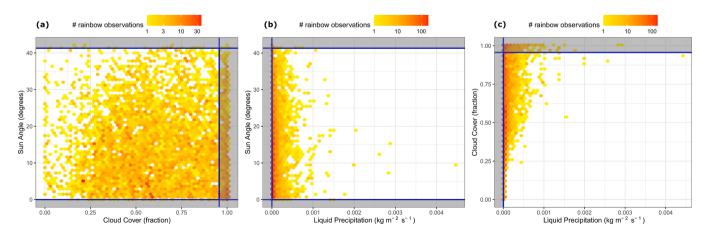


Fig. 3. Environmental conditions under which observed rainbows occurred and rainbow prediction model parameters. Density plots of cloud cover-sun angle (a), precipitation-sun angle (b), and precipitation-cloud cover (c) conditions under which the 7,094 photographed rainbows in our training and testing database occurred. The solid blue lines illustrate recursive partitioning and regression tree model cutoffs, and the grey shaded areas indicate conditions under which rainbows are not predicted by the model. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

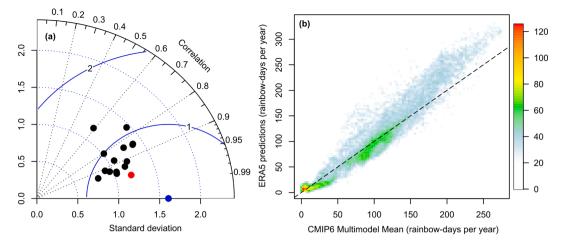


Fig. 4. Rainbow prediction accuracy. (a) A comparison of 13 CMIP6 Earth System Models (Table 1) to ERA5 reanalysis data (Hersbach et al., 2018) using a Taylor diagram that indicates correlation (curved axis), ratio of standard deviations (x-y axes), and root mean squared error (blue curve). The blue circle indicates a perfect fit, the red circle depicts the multi-model mean, and the black circles represent a comparison of each Earth System Model to ERA5 data. (b) Relationship between the CMIP6 multi-model mean and the ERA5 reanalysis prediction of mean annual rainbow-days per grid cell from 1996 to 2005 (Pearson's correlation coefficient = 0.96). Dashed line indicates 1:1 relationship. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of human population, compared to circa-2000, opportunities for the average person to view rainbows in 2100 also increase under all future scenarios, from +1.9 (SSP 8.5) to +4.0 (SSP 2.6) more rainbow-days per year (Fig. 6b). This increase is just 36–92 % of the net area-weighted change because relatively fewer (more) people will live where increases (decreases) in rainbow occurrence are projected to be greatest.

However, these small net changes mask substantial redistribution of rainbows across space. Around 21–34 % of land areas will lose rainbow-days and 66–79 % will gain rainbow-days, with relatively more locations experiencing loss or gain under higher emission futures (Fig. 6a). Under the highest emission future (SSP5 8.5), hotspots of decline include the Mediterranean, much of Brazil and northeast South America, southern Australia, and parts of Central and Southern Africa (Fig. 7). Rainbow-gain hotspots are expected in northern North America (e.g., Alaska) and Eurasia (e.g., northern Norway), the Korean Peninsula, Japan, the Tibetan Plateau, and eastern Borneo (Fig. 7).

4. Discussion

With a dataset of temporally and geographically located rainbow observations, we trained a model of rainbow occurrence and then applied this model to gridded climate projections to understand the current and potential future distribution of rainbows. To our knowledge, this is the first attempt to map rainbow occurrence, and thus represents a foray into better understanding how anthropogenic climate change may alter the distribution of the rainbow, an atmospheric optical phenomenon that we argue provides cultural ecosystem services. In this discussion, we explore the possible drivers of observed changes in rainbows, the implications of these changes for humans, and some limitations of our research.

4.1. Factors associated with rainbow occurrence and change

Rainbows occur within a simple "envelope" of conditions defined by physics, which was relatively well captured by our model when applied to reanalysis and Earth System Model data. Yet, the complexity of specific interactions between sun angle, cloud cover, and liquid precipitation across time (e.g., the relative amount of precipitation that occurs when cloud cover is very high, and the diurnal patterns of precipitation and cloud cover that interact with sun angle across seasons) prevents precisely linking such conditions to the distribution of annual rainbowdays produced by the current application of our rainbow prediction

model

Nevertheless, we observe certain meteorological commonalities between regions with very low and high rainbow occurrence circa-2000. Specifically, annual rainbow-days were lowest in polar regions with little liquid precipitation and desert areas with low overall precipitation. Rainbow occurrence was greatest in many coastal tropical regions and some other parts of the wet tropics which all have - relative to the global distribution - high levels of annual liquid precipitation. Yet, rainbow frequency varied widely across wet tropical locations. For instance, it was relatively low in Borneo, potentially because of high year-round cloud cover levels over the island (Vignesh et al., 2020).

Locations of projected rainbow loss and gain under SSP5-8.5 also share certain general attributes. Most hotspots of rainbow loss are projected to have lower total precipitation by 2100 except those in Central Africa, Madagascar, and central South America (Gutiérrez et al., 2021; Iturbide et al., 2021), and all are projected to have more annual dry days (Douville et al., 2021) and less total annual cloud cover (IPCC, 2021; Ma et al., 2022). Rainbow gain hotspots are mostly located at higher latitudes or at very high elevations (i.e., the Tibetan Plateau), and thus gains may be partially linked to projected increases in overall precipitation (Gutiérrez et al., 2021; Iturbide et al., 2021) and dry days (Douville et al., 2021) in these locations, as well as a change in the phase of precipitation from snow to rain (Bintanja, 2018). Yet two rainbow gain hotspots - eastern Borneo and northern Japan - will see overall precipitation increases but more dry days per year (Douville et al., 2021; Gutiérrez et al., 2021; Iturbide et al., 2021).

4.2. Implications of rainbow change for human wellbeing

Our projections indicate that under all climate change scenarios, by 2100 the average human will have more opportunities to see rainbows than in year 2000. Anthropogenic climate change will bring new rainbow-viewing opportunities for people in northern latitudes, where more overall and liquid precipitation creates a greater likelihood of rainbow occurrence (Bintanja, 2018; IPCC, 2021). However, certain heavily populated locations, such as the Mediterranean, are likely to see a substantial reduction in rainbow occurrence by 2100. Given that human connection with nature is a critical dimension of environmental concern and happiness (Soga and Gaston, 2016), further research may be needed to understand whether and how these predicted changes to rainbow occurrence will alter human interaction with non-human nature, and how these outcomes vary across multiple dimensions including

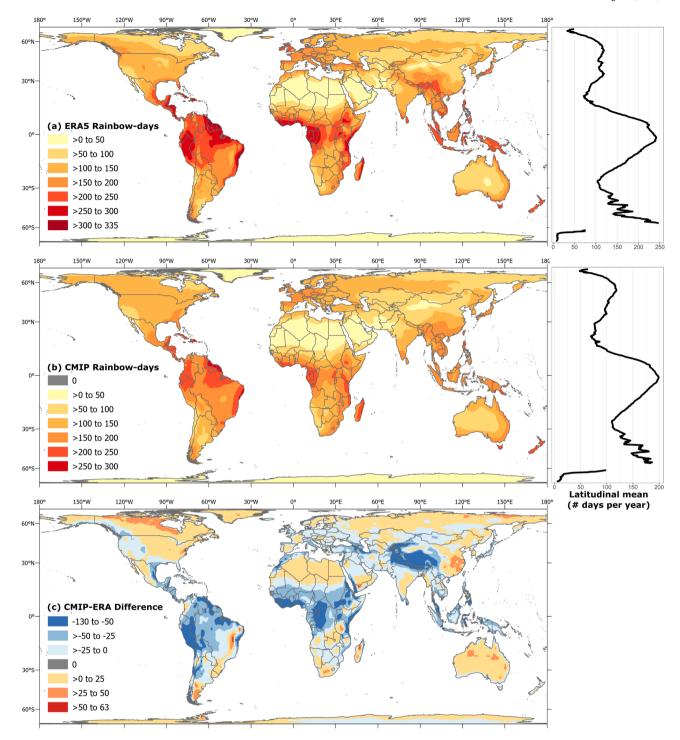


Fig. 5. Comparison of circa-2000 rainbow-days across global lands. Annual rainbow-days for the 1996–2005 period were predicted from (a) ERA5 reanalysis and (b) the multi-model mean of 13 CMIP6 Earth System Models. (c) The difference in rainbow-days between the CMIP6 multi-model mean and ERA5, where positive values indicate more predicted rainbows from CMIP6. Latitudinal graphs represent means across land area at each latitude, and the gap in the black line in the southern hemisphere is due to no land area at that latitude. (For interpretation of the colors in this figure, the reader is referred to the web version of this article.)

space, peoples' values, and wealth (Tschakert et al., 2019). As with other climate change related risks (Hess et al., 2008), the implications of a change in rainbow occurrence are likely to be place-specific and could interact with the positive or negative perceptions of rainbows in that place as well as other psychological considerations such as loss aversion and the relative value of rare phenomena (Courchamp et al., 2006; Wang et al., 2017).

It is also relevant to consider effects on economies, for example via changes in tourist-based income and property values. In locations of severe rainbows decline where economies partly depend on nature-based tourism and rainbows play an important role in mythologies connected to place (e.g., Greece), people may consider undertaking mitigation activities. These could include ensuring that good rainbow-viewing locations remain unobstructed or constructing water features (e.g., fountains) that can produce rainbows. Adaptation is also possible if people alter their travel choices to target locations where rainbows are more common or their outdoor activities to maximize locations and times where rainbows are likely to occur. Parallel global changes such as

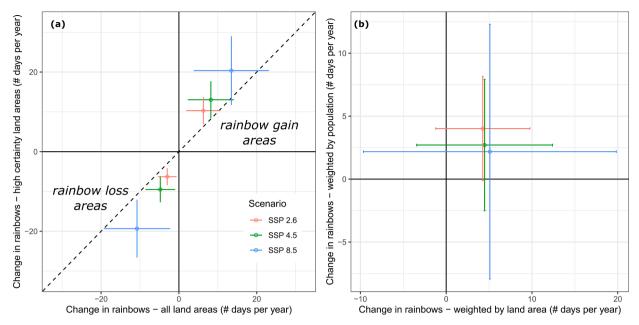


Fig. 6. Projected future changes in the occurrence of rainbows. These plots depict the CMIP6 multi-model global mean (center of cross) and standard deviation of the mean (crosshairs) of change in rainbow-days from circa-2000 to circa-2100. (a) Depicts all grid cells versus only high certainty cells (i.e., those for which the multi-model standard deviation did not exceed the multi-model mean) divided into locations that experienced gains and losses to demonstrate the spatial heterogeneity of directional change (diagonal line = 1:1 ratio). (b) Depicts all grid cells, and compares the multi-model mean and standard deviation weighted by grid cell land area versus weighted by projected grid cell human population in 2100. (For interpretation of the colors in this figure, the reader is referred to the web version of this article.)

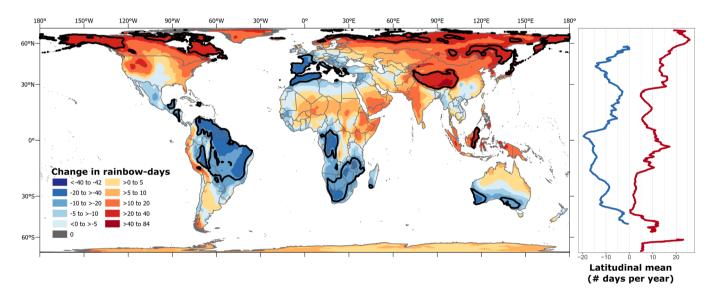


Fig. 7. Potential future changes in global rainbow distribution under the high emissions scenario. Map of multi-model mean change in annual rainbow-days from circa-2000 to circa-2100 under SSP5-8.5. Black polygons indicate "hotspots" of change with probability > 0.90 that the value is a statistical outlier from a t distribution. Latitudinal graph represents means across land areas at each latitude, and the gap in the red line in the southern hemisphere is due to no land area at that latitude. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

urbanization and increasing use of technology (Kellert et al., 2017) may also reduce rainbow viewing opportunities. For instance, people living in cities may not be able to see rainbows that are present due to buildings blocking their view, and individuals who spend more time indoors will have fewer chances to see real rainbows.

However, given the gradual nature of likely climate change-induced alterations to rainbow occurrence, it is possible that people will easily adapt to or even fail to notice such changes. For instance, research on human perceptions of temperature indicates that recent experience sets a subjective "baseline" by which people evaluate the future (Moore et al., 2019).

4.3. Limitations

Our results are subject to several limitations and uncertainties. First, the distribution of the data used to train and validate the model may be biased. Physical barriers such as mountains and buildings can impede views of rainbows. Thus, rainbows that occurred near urban and mountainous areas may be underrepresented in training data. We did not include air pollution, which can prevent rainbow viewing, in our model. Moreover, we only used photographs labeled with the English word "rainbow", and thus likely under-sampled in locations where people tagged rainbows with other languages or in regions where Flickr

was not widely used during the study time frame. For instance, we have relatively few training data points from Africa and Russia (Fig. 2). Because cloud fraction, precipitation, and sun angle co-occurrence vary across regions and latitudes, our rainbow training and testing sample is unlikely to represent the actual distribution of rainbow and non-rainbow conditions globally and the accuracy of our model may thus be lower in places with conditions that were not represented in our training dataset. Moreover, while we took steps to minimize the likelihood that photograph upload location differed from the location where the photograph was collected, it is possible that the locations of some of the photographs were inaccurate. Finally, our non-rainbow dataset almost certainly included some false negatives (i.e., rainbows), likely at a higher rate than false positives in our Flickr-derived dataset. This may have biased our model toward rainbow under-prediction.

Another limitation relates to the climatic variables used to build the empirical model of rainbows. Given our motivation to evaluate the global spatial distribution of rainbows, we used reanalysis data, which combine observations of weather with a dynamic model to create a global, gridded, gapless reconstruction of recent past climate. This interpolation may add errors to the conditions under which rainbows may occur. Despite these known sources of error in training and climate data, our model predicted the actual occurrence of rainbows with good accuracy, yielding results that largely conform to the theoretical expectations of rainbow occurrence (Fig. 1, Fig. 3)(Businger, 2021).

Finally, the CMIP6 model outputs contain known biases for the timing of variables we included in our model, which may have interacted with sun angle. For instance, CMIP6 models simulate relatively more nighttime and fewer daytime clouds than observed (Chen et al., 2022), and tend to produce peak precipitation too early in the day (Christopoulos and Schneider, 2021). Such diurnal biases could explain the imperfect relationship between annual rainbow-days derived from ERA5 reanalysis and the CMIP6 multi-model mean (Fig. 4b).

4.4. Conclusion

We find that the ongoing emission of greenhouse gasses due to human activity could influence an aspect of the climate system that humans have held dear throughout history and around the world: rainbows. While many world regions, particularly those at high latitudes, will gain rainbow-days, several densely populated places are projected to be hotspots of rainbow loss. Our results underscore the fact that climate change will alter not just tangible earth system dynamics with clear socio-economic implications, but also parts of the earth system that we cannot touch, and that may affect us in more subtle ways. Although our focus here was rainbows, other non-tangibles (e.g., sound) that connect people and their environments will be affected by a changing climate (Krause and Farina, 2016). There is an urgent need to better understand the magnitude, location, and timing of these changes, as well as whether and how such changes will alter human wellbeing.

CRediT authorship contribution statement

Kimberly M. Carlson: Conceptualization, Formal analysis, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. Camilo Mora: Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. Jinwen Xu: Data curation, Formal analysis, Investigation, Visualization, Writing – review & editing. Renee O. Setter: Data curation, Investigation, Writing – review & editing. Michelle Harangody: Data curation, Investigation, Writing – review & editing. Erik C. Franklin: Data curation, Methodology, Writing – review & editing. Michael B. Kantar: Data curation, Writing – review & editing. Zachary M. Menzo: Data curation, Investigation, Writing – review & editing. Daniele Spirandelli: Data curation, Writing – review & editing. Daniele Spirandelli: Data curation, Writing – review & editing. David Schanzenbach:

Investigation, Writing – review & editing. **C. Courtlandt Warr:** Data curation, Software, Writing – review & editing. **Amanda E. Wong:** Data curation, Investigation, Writing – review & editing. **Steven Businger:** Data curation, Methodology, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

Thanks to the World Climate Research Programme's Working Group on Coupled Modeling for CMIP6, climate modeling groups for model outputs, S. Cleveland and R. Merrill from the University of Hawai'i Information Technology Services for the technical support, Hawai'i Sea-Grant for computers used in analyses, and two anonymous reviewers for constructive feedback. This work was supported in part through the NYU IT High Performance Computing resources, services, and staff expertise. MBK was supported by USDA Cooperative State Research, Education and Extension (CSREES) Grant/Award Number HAW08039-H.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2022.102604.

References

- Adger, W.N., Barnett, J., Brown, K., Marshall, N., O'brien, K., 2013. Cultural dimensions of climate change impacts and adaptation. Nat. Clim. Change 3, 112–117. https:// doi.org/10.1038/nclimate1666
- Anderson, B., 2020. Cultural geography III: the concept of 'culture'. Prog. Hum. Geogr. 44, 608–617. https://doi.org/10.1177/0309132519856264.
- Associated Press, 2013. Hawaii Bringing 'Rainbow' back to Warriors Nicknames. USA Today, Honolulu, HI.
- Bintanja, R., 2018. The impact of Arctic warming on increased rainfall. Sci. Rep. 8, 1–6. https://doi.org/10.1038/s41598-018-34450-3.
- Boucher, O., Randall, D., Artaxo, P., Bretherton, C., Feingold, G., Forster, P., Kerminen, V.-M., Kondo, Y., Liao, H., Lohmann, U., (2013) Clouds and aerosols, in: Stocker, T. F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung,, A. Nauels, Y.X., V. Bex, P.M. Midgley (Eds.), Climate change 2013: the physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, pp. 571-657.
- Boucher, O.D., Sébastien; Levavasseur, Guillaume; Cozic, Anne; Caubel, Arnaud; Foujols, Marie-Alice; Meurdesoif, Yann; Cadule, Patricia; Devilliers, Marion; Ghattas, Josefine; Lebas, Nicolas; Lurton, Thibaut; Mellul, Lidia; Musat, Ionela; Mignot, Juliette; Cheruy, Frédérique, (2018) IPSL IPSL-CM6A-LR model output prepared for CMIP6 CMIP. Earth System Grid Federation, 10.22033/ESGF/CMIP6.1534.
- Businger, S., 2021. The secrets of the best rainbows on earth. Bull. Am. Meteorol. Soc. 102, E338–E350. https://doi.org/10.1175/BAMS-D-20-0101.1.
- Byun, Y.-H.L., Yoon-Jin; Sung, Hyun Min; Kim, Jisun; Sun, Minah; Kim, Byeong-Hyeon, (2019) NIMS-KMA KACE1.0-G model output prepared for CMIP6 CMIP. Earth System Grid Federation, 10.22033/ESGF/CMIP6.2241.
- Cao, J.W., Bin, (2019) NUIST NESMv3 model output prepared for CMIP6 CMIP. Earth System Grid Federation, 10.22033/ESGF/CMIP6.2021.
- Chan, K.M., Balvanera, P., Benessaiah, K., Chapman, M., Díaz, S., Gómez-Baggethun, E., Gould, R., Hannahs, N., Jax, K., Klain, S., 2016. Opinion: why protect nature? Rethinking values and the environment. Proc. Natl. Acad. Sci. USA 113, 1462–1465. https://doi.org/10.1073/pnas.1525002113.
- Chapin III, F.S., Knapp, C.N., 2015. Sense of place: A process for identifying and negotiating potentially contested visions of sustainability. Environ. Sci. Policy 53, 38–46. https://doi.org/10.1016/j.envsci.2015.04.012.
- Chen, G., Wang, W.C., Bao, Q., Li, J., 2022. Evaluation of simulated cloud diurnal variation in CMIP6 climate models. J. Geophys. Res.: Atmos. 127 https://doi.org/ 10.1029/2021JD036422 e2021JD036422.
- Christopoulos, C., Schneider, T., 2021. Assessing biases and climate implications of the diurnal precipitation cycle in climate models. Geophys. Res. Lett. 48 https://doi.org/ 10.1029/2021GL093017 e2021GL093017.
- Corripio, J.G., (2020) insol: Solar Radiation, 1.2.2 ed, https://cran.r-project.org/web/packages/insol/index.html.

- Courchamp, F., Angulo, E., Rivalan, P., Hall, R.J., Signoret, L., Bull, L., Meinard, Y., 2006. Rarity value and species extinction: the anthropogenic Allee effect. PLoS Biol. 4, ed. 15.
- Darrouzet-Nardi, A., (2018) Package 'hotspots', 1.0.3 ed, https://cran.r-project.
- Dix, M.B., Doahua; Dobrohotoff, Peter; Fiedler, Russell; Harman, Ian; Law, Rachel; Mackallah, Chloe; Marsland, Simon; O'Farrell, Siobhan; Rashid, Harun; Srbinovsky, Jhan; Sullivan, Arnold; Trenham, Claire; Vohralik, Peter; Watterson, Ian; Williams, Gareth; Woodhouse, Matthew; Bodman, Roger; Dias, Fabio Boeira; Domingues, Catia; Hannah, Nicholas; Heerdegen, Aidan; Savita, Abhishek; Wales, Scott; Allen, Chris; Druken, Kelsey; Evans, Ben; Richards, Clare; Ridzwan, Syazwan Mohamed; Roberts, Dale; Smillie, Jon; Snow, Kate; Ward, Marshall; Yang, Rui, (2019) CSIRO-ARCCSS ACCESS-CM2 model output prepared for CMIP6 CMIP. Earth System Grid Federation, 10.22033/ESGF/CMIP6.2281.
- Douville, H., K. Raghavan, J. Renwick, R.P. Allan, P.A. Arias, M. Barlow, R. Cerezo-Mota, A. Cherchi, T.Y. Gan, J. Gergis, D. Jiang, A. Khan, W. Pokam Mba, D. Rosenfeld, J. Tierney, and O. Zolina, (2021) 2021: Water Cycle Changes, in: Masson-Delmotte, V. P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (Ed.), Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1055–1210.
- Dronova, I., 2019. Landscape beauty: a wicked problem in sustainable ecosystem management? Sci. Total Environ. 688, 584–591.
- EC-Earth Consortium (EC-Earth), 2019. EC-Earth-Consortium EC-Earth3 model output prepared for CMIP6 CMIP. Earth System Grid Federation. https://doi.org/10.22033/ ESGF/CMIP6.181.
- Enriquez-Alonso, A., Sanchez-Lorenzo, A., Calbó, J., González, J.-A., Norris, J.R., 2016. Cloud cover climatologies in the Mediterranean obtained from satellites, surface observations, reanalyses, and CMIP5 simulations: validation and future scenarios. Clim. Dyn. 47, 249–269. https://doi.org/10.1007/s00382-015-2834-4.
- European Centre for Medium-Range Weather Forecasts, (2013) Reference Guide: Precipitation, https://confluence.ecmwf.int/display/EMOS/Precipitation.
- Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J., Taylor, K.E., 2016. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geosci. Model Dev. 9, 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016.
- Gedzelman, S.D., Vollmer, M., 2008. Atmospheric optical phenomena and radiative transfer. Bull. Am. Meteorol. Soc. 89, 471–486. https://doi.org/10.1175/BAMS-89-4-471
- Gould, R.K., Bremer, L.L., Pascua, P.A., Meza-Prado, K., 2020. Frontiers in cultural ecosystem services: toward greater equity and justice in ecosystem services research and practice. Bioscience 70, 1093–1107. https://doi.org/10.1093/biosci/biaa112.
- Gutiérrez, J.M., R.G. Jones, G.T. Narisma, L.M. Alves, M. Amjad, I.V. Gorodetskaya, M. Grose, N.A.B. Klutse, S. Krakovska, J. Li, D. Martínez-Castro, L.O. Mearns, S.H. Mernild, T. Ngo-Duc, B. van den Hurk, and J.-H. Yoon, (2021) 2021: Atlas, in: Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L.Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T. K.Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (Ed.), Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.
- Haider, W., Knowler, D., Trenholm, R., Moore, J., Bradshaw, P., Lertzman, K., 2019. Climate change, increasing forest fire incidence, and the value of visibility: evidence from British Columbia, Canada. Can. J. For. Res. 49, 1242–1255. https://doi.org/ 10.1139/cifr-2018-0309.
- Haines-Young, R., Potschin, M., 2010. The links between biodiversity, ecosystem services and human well-being. Ecosyst. Ecol.: A New Synthesis 1, 110–139.
- Hardwick, J., 2004. The subtlety of rainbows. Phys. World 17, 29. https://doi.org/ 10.1088/2058-7058/17/2/33.
- Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., Thépaut, J-N, (2018) ERA5 hourly data on single levels from 1979 to present, Copernicus Climate Change Service (C3S) Climate Data Store (CDS), 10.24381/cds. adbb2d47.
- Hess, J.J., Malilay, J.N., Parkinson, A.J., 2008. Climate change: the importance of place. Am. J. Prev. Med. 35, 468–478. https://doi.org/10.1016/j.amepre.2008.08.024.
- Himes, A., Muraca, B., 2018. Relational values: the key to pluralistic valuation of ecosystem services. Curr. Opin. Environ. Sustain. 35, 1–7. https://doi.org/10.1016/ j.cosust.2018.09.005.
- Hyslop, N.P., 2009. Impaired visibility: the air pollution people see. Atmos. Environ. 43, 182–195. https://doi.org/10.1016/j.atmosenv.2008.09.067.
- IPCC, (2021) Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change in: Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J.B.R., Maycock, T.K., Waterfield, T., Yelekçi, O., Yu, R., Zhou, B. (Eds.).
- Iturbide, M., Fernández, J., Gutiérrez, J.M., Bedia, J., Cimadevilla, E., Díez-Sierra, J., Manzanas, R., Casanueva, A., Baño-Medina, J., Milovac, J., Herrera, S., Cofiño, A.S., San Martín, D., García-Díez, M., Hauser, M., Huard, D., Yelekci, Ö., 2021. Repository supporting the implementation of FAIR principles in the IPCC-WG1 Atlas. Zenodo. https://doi.org/10.5281/zenodo.3691645.
- Jenkins, K., (2019) Songs about rainbows. SAGE Publications Sage UK: London, England, pp. 329-331, 10.1177/1039856219859191.

- Jones, B., O'Neill, B.C., 2016. Spatially explicit global population scenarios consistent with the Shared Socioeconomic Pathways. Environ. Res. Lett. 11, 084003 https:// doi.org/10.1088/1748-9326/11/8/084003.
- Jungclaus, J.B., Matthias; Wieners, Karl-Hermann; Wachsmann, Fabian; Schupfner, Martin; Legutke, Stephanie; Giorgetta, Marco; Reick, Christian; Gayler, Veronika; Haak, Helmuth; de Vrese, Philipp; Raddatz, Thomas; Esch, Monika; Mauritsen, Thorsten; von Storch, Jin-Song; Behrens, Jörg; Brovkin, Victor; Claussen, Martin; Crueger, Traute; Fast, Irina; Fiedler, Stephanie; Hagemann, Stefan; Hohenegger, Cathy; Jahns, Thomas; Kloster, Silvia; Kinne, Stefan; Lasslop, Gitta; Kornblueh, Luis; Marotzke, Jochem; Matei, Daniela; Meraner, Katharina; Mikolajewicz, Uwe; Modali, Kameswarrao; Müller, Wolfgang; Nabel, Julia; Notz, Dirk; Peters-von Gehlen, Karsten; Pincus, Robert; Pohlmann, Holger; Pongratz, Julia; Rast, Sebastian; Schmidt, Hauke; Schnur, Reiner; Schulzweida, Uwe; Six, Katharina; Stevens, Bjorn; Voigt, Aiko; Roeckner, Erich, (2019) MPI-M MPIESM1.2-HR model output prepared for CMIP6 CMIP. Earth System Grid Federation, 10.22033/ESGF/CMIP6.741.
- Kellert, S.R., Case, D.J., Escher, D., Daniel J. Witter, Mikels-Carrasco, J., Seng, P.T., (2017) The Nature of Americans: Disconnection and Recommendations for Reconnection, https://natureofamericans.org/.
- Krause, B., Farina, A., 2016. Using ecoacoustic methods to survey the impacts of climate change on biodiversity. Biol. Conserv. 195, 245–254. https://doi.org/10.1016/j. biocon.2016.01.013.
- Kuruppu, N., Liverman, D., 2011. Mental preparation for climate adaptation: the role of cognition and culture in enhancing adaptive capacity of water management in Kiribati. Global Environ. Change 21, 657–669. https://doi.org/10.1016/j. gloenycha.2010.12.002.
- Lee, R.L., Fraser, A.B. (2001) The rainbow bridge: rainbows in art, myth, and science. Penn State Press.
- Lehner, F., Deser, C., Maher, N., Marotzke, J., Fischer, E.M., Brunner, L., Knutti, R., Hawkins, E., 2020. Partitioning climate projection uncertainty with multiple large ensembles and CMIP5/6. Earth Syst. Dyn. 11, 491–508. https://doi.org/10.5194/ esd-11-491-2020
- Lovato, T.P., Daniele; Butenschön, Momme, (2021) CMCC CMCC-ESM2 model output prepared for CMIP6 CMIP. Earth Syst. Grid Federation, 10.22033/ESGF/ CMIP6.13164.
- Lovato, T.P., Daniele, (2020) CMCC CMCC-CM2-SR5 model output prepared for CMIP6 CMIP. Earth System Grid Federation, 10.22033/ESGF/CMIP6.1362.
- Löwenstein, J., 1961, Rainbow and serpent, Anthropos 31–40.
- Ma, J., Feng, J., Kang, I.-S., Collins, M., Watanabe, M., Li, J., Zhang, Y. (2022) Percentage change patterns in cloud fraction effectively constrain global cloud feedback. 10.21203/rs.3.rs-1377524/v1.
- MacCannell, D., 2018. Rainbows: Nature and Culture. Reaktion Books Ltd, London. Millennium Ecosystem Assessment, 2005. Chapter 1: MA Conceptual Framework. Ecosystems and human well-being. Island Press, Washington, DC, pp. 25–36.
- Moore, F.C., Obradovich, N., Lehner, F., Baylis, P., 2019. Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change. Proc. Natl. Acad. Sci. 116, 4905–4910. https://doi.org/10.1073/pnas.1816541116.
- Mora, C., Spirandelli, D., Franklin, E.C., Lynham, J., Kantar, M.B., Miles, W., Smith, C.Z., Freel, K., Moy, J., Louis, L.V., 2018. Broad threat to humanity from cumulative climate hazards intensified by greenhouse gas emissions. Nat. Clim. Change 8, 1062–1071. https://doi.org/10.1038/s41558-018-0315-6.
- Pendergrass, A.G., Hartmann, D.L., 2014. Changes in the distribution of rain frequency and intensity in response to global warming. J. Clim. 27, 8372–8383. https://doi. org/10.1175/JCLI-D-14-00183.1.
- Russell, R., Guerry, A.D., Balvanera, P., Gould, R.K., Basurto, X., Chan, K.M., Klain, S., Levine, J., Tam, J., 2013. Humans and nature: how knowing and experiencing nature affect well-being. Annu. Rev. Environ. Resour. 38, 473–502. https://doi.org/ 10.1146/annurev-environ-012312-110838.
- Satz, D., Gould, R.K., Chan, K., Guerry, A., Norton, B., Satterfield, T., Halpern, B.S., Levine, J., Woodside, U., Hannahs, N., 2013. The challenges of incorporating cultural ecosystem services into environmental assessment. Ambio 42, 675–684. https://doi.org/10.1007/s13280-013-0386-6.
- Semmler, T.D., Sergey; Rackow, Thomas; Sidorenko, Dmitry; Barbi, Dirk; Hegewald, Jan; Sein, Dmitri; Wang, Qiang; Jung, Thomas, (2018) AWI AWI-CMI.1MR model output prepared for CMIP6 CMIP. Earth System Grid Federation, 10.22033/ESGF/CMIP6.359.
- Soga, M., Gaston, K.J., 2016. Extinction of experience: the loss of human-nature interactions. Front. Ecol. Environ. 14, 94–101. https://doi.org/10.1002/fee.1225.
- Tatebe, H.W., Masahiro, 2018. MIROC MIROC6 model output prepared for CMIP6 CMIP. Earth Syst. Grid Federation. https://doi.org/10.22033/ESGF/CMIP6.881.
- Therneau, T., Atkinson, B., Ripley, B., (2022) An Introduction to Recursive Partitioning Using the RPART Routines, 4.1.16 ed, https://CRAN.R-project.org/package=rpart.
- Thieurmel, B., Elmarhraoui, A., (2019) suncalc: Compute Sun Position, Sunlight Phases, Moon Position and Lunar Phase, 0.5.0 ed, https://cran.r-project.org/web/packages/suncalc/suncalc.pdf.
- Tribot, A.-S., Deter, J., Mouquet, N., 2018. Integrating the aesthetic value of landscapes and biological diversity. Proc. Royal Soc. B: Biol. Sci. 285, 20180971.
- Tschakert, P., Ellis, N.R., Anderson, C., Kelly, A., Obeng, J., 2019. One thousand ways to experience loss: a systematic analysis of climate-related intangible harm from around the world. Global Environ. Change 55, 58–72. https://doi.org/10.1016/j. gloenvcha.2018.11.006.
- ${\rm USGS}$ (n.d.) Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global data, 10.5066/F7PR7TFT.
- Veland, S., Howitt, R., Dominey-Howes, D., Thomalla, F., Houston, D., 2013. Procedural vulnerability: understanding environmental change in a remote indigenous community. Global Environ. Change 23, 314–326. https://doi.org/10.1016/j. gloenvcha.2012.10.009.

- Vignesh, P.P., Jiang, J.H., Kishore, P., Su, H., Smay, T., Brighton, N., Velicogna, I., 2020.

 Assessment of CMIP6 cloud fraction and comparison with satellite observations.

 Earth Space Sci. 7 https://doi.org/10.1029/2019EA000975 e2019EA000975.
- Vince, G., (2020) Rainbows as signs of thank you, hope and solidarity, Culture in Quarantine, www.bbc.com.
- Wang, M., Rieger, M.O., Hens, T., 2017. The impact of culture on loss aversion. J. Behav. Decis. Making 30, 270–281. https://doi.org/10.1002/bdm.1941.
- White, N.I., Hand, W.D. (2013) The Frank C. Brown Collection of NC Folklore: Vol. VII:
 Popular Beliefs and Superstitions from North Carolina, pt. 2. Duke University Press.
- Wieners, K.-H.G., Marco; Jungclaus, Johann; Reick, Christian; Esch, Monika; Bittner, Matthias; Legutke, Stephanie; Schupfner, Martin; Wachsmann, Fabian; Gayler, Veronika; Haak, Helmuth; de Vrese, Philipp; Raddatz, Thomas; Mauritsen, Thorsten; von Storch, Jin-Song; Behrens, Jörg; Brovkin, Victor; Claussen, Martin; Crueger, Traute; Fast, Irina; Fiedler, Stephanie; Hagemann, Stefan; Hohenegger, Cathy; Jahns, Thomas; Kloster, Silvia; Kinne, Stefan; Lasslop, Gitta; Kornblueh, Luis; Marotzke, Jochem; Matei, Daniela; Meraner, Katharina; Mikolajewicz, Uwe; Modali, Kameswarrao; Müller, Wolfgang; Nabel, Julia; Notz, Dirk; Peters-von Gehlen,
- Karsten; Pincus, Robert; Pohlmann, Holger; Pongratz, Julia; Rast, Sebastian; Schmidt, Hauke; Schnur, Reiner; Schulzweida, Uwe; Six, Katharina; Stevens, Bjorn; Voigt, Aiko; Roeckner, Erich, (2019) MPI-M MPIESM1.2-LR model output prepared for CMIP6 CMIP. Earth System Grid Federation, 10.22033/ESGF/CMIP6.742.
- Xin, X.Z., Jie; Zhang, Fang; Wu, Tongwen; Shi, Xueli; Li, Jianglong; Chu, Min; Liu, Qianxia; Yan, Jinghui; Ma, Qiang; Wei, Min, (2018) BCC BCC-CSM2MR model output prepared for CMIP6 CMIP. Earth Syst. Grid Federation 10.22033/ESGF/CMIP6.1725.
- Yukimoto, S.K., Tsuyoshi; Kawai, Hideaki; Oshima, Naga; Yoshida, Kohei; Urakawa, Shogo; Tsujino, Hiroyuki; Deushi, Makoto; Tanaka, Taichu; Hosaka, Masahiro; Yoshimura, Hiromasa; Shindo, Eiki; Mizuta, Ryo; Ishii, Masayoshi; Obata, Atsushi; Adachi, Yukimasa, (2019) MRI MRI-ESM2.0 model output prepared for CMIP6 CMIP. Earth Syst. Grid Federation, 10.22033/ESGF/CMIP6.621.
- Zhang, X., Wan, H., Zwiers, F.W., Hegerl, G.C., Min, S.K., 2013. Attributing intensification of precipitation extremes to human influence. Geophys. Res. Lett. 40, 5252–5257. https://doi.org/10.1002/grl.51010.