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To cite this article: A Stechemesser *et al* 2021 *Environ. Res. Lett.* **16** 114001

ENVIRONMENTAL RESEARCH
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OPEN ACCESS

RECEIVED
30 July 2021

REVISED
16 September 2021

ACCEPTED FOR PUBLICATION
21 September 2021

PUBLISHED
14 October 2021

LETTER

Strong increase of racist tweets outside of climate comfort zone in Europe

A Stechemesser[1,2], L Wenz[1,3,4,*], M Kotz[1,2] and A Levermann[1,2,5]

1 Potsdam Institute for Climate Impact Research, PO Box 60 12 03, 14412 Potsdam, Germany
2 Institute of Physics, Potsdam University, Campus Golm, Haus 28, Karl-Liebknecht-Straße 24/25, 14476 Potsdam, Germany
3 Mercator Research Institute on Global Commons and Climate Change, EUREF Campus 19, Torgauer Straße 12-15, 10829 Berlin, Germany
4 Department of Agricultural and Resource Economics, University of California Berkeley, 714 University Hall #3310, University of California, Berkely, CA, 94720-3310, United States of America
5 The Earth Institute, Columbia University, Hogan Hall, 2910 Boradway, Level A, Mail Code: 3277, New York, NY, 10025, United States of America
* Author to whom any correspondence should be addressed.

E-mail: leonie.wenz@pik-potsdam.de

Keywords: climate change, cyber racism, Twitter, temperature, conflict

Supplementary material for this article is available online

Abstract

Ambient temperature has been identified as a potential cause for human conflict in a variety of studies. Conflict is no longer limited to the physical space but exists in the form of hate and discrimination on social media. Here we provide evidence that the amount of racist and xenophobic content posted to the social media platform Twitter is nonlinearly influenced by temperature. Exploiting the linguistic plurality of Europe, we statistically analyze daily temperature data and more than ten million racist tweets from six different countries spanning several climate zones for the years 2012–2018. Using a fixed-effects panel regression model that utilizes exogenous variation in local weather and controls for unobserved omitted variables, we identify the effect of population-weighted daily average temperature on the daily number of racist tweets and likes. We find a quasi-quadratic temperature response of racist tweets that is inversely proportional to the temperature distribution. Fewest racist tweets and likes are found for daily average temperatures between 5 °C and 11 °C, i.e. temperatures that are frequently experienced. Temperatures warmer or colder than that are associated with steep, nonlinear increases. Analyses at the country-level confirm this climate comfort zone of 5 °C–11 °C across different European climatic zones. In the Southern European countries this is colder than the most frequently experienced temperatures, pointing to possible limits of adaptation. Within the next 30 years, the number of days outside this climate comfort zone, weighted by the identified temperature-racist-tweet response curve, will increase across parts of Europe, indicating that rising temperatures could aggravate xenophobia and racism in social media.

1. Introduction

Weather is undoubtedly one of the key influences on human behavior. The Roman philosopher Cicero (106–43 B.C.) already observed that: 'The minds of men do in the weather share. Dark or serene as the day's foul or fair' [1]. Links between human aggression and temperature have been found across multiple disciplines. Numerous psychological studies show that hot temperatures enhance aggression [2–6], but similar evidence was found in for instance the field of international affairs [7] and forensic psychiatrics and neurology [8]. A growing body of multidisciplinary quantitative studies comparing changes in weather observations to those in social data [9–11] indicates that deviations from mild weather conditions increase conflict risk around the globe [12–14]. More specifically, temperature anomalies have been found to increase violent crime [15, 16] and rape [17] in the USA, civil war incidence and armed conflict in Africa [18–23] and the Middle East [22, 24, 25] and political and inter-group violence in East Africa and

Kenya [19, 20, 26]. The thus identified link between aggression and temperature anomalies suggests that temperature may be a potential driver of cyber racism as well.

Racially offensive and discriminatory language on the internet, often referred to as cyber racism or cyber xenophobia, has become a prevalent problem in the digital age [27–29]. Racially targeted aggressions on social media have shown to have mental health impacts [30, 31] such as heightened anxiety, depression or self-harm [32]. In addition to its direct online-consequence, studies suggest that cyber racism also leads to hate crimes in the physical space [33]. Against the backdrop of the Covid-19 pandemic, the problem of cyber racism has aggravated through increased Sinophobia online [34, 35]. Finding potential drivers for this aggressive behavior is crucial for addressing the issue of online and offline racism in the future.

Here, we examine the effect of temperature on the occurrence and acceptance of racist, xenophobic and religiously discriminating posts on the social media platform Twitter across six countries representing different European climatic zones between the years 2012 and 2018 using fixed-effects panel regression models. Twitter is one of the most commonly used social media platforms with more than 300 million active users worldwide [36], making it suitable for a representative analysis of online discourse. Statistical analysis of social media data in general [37–39] and Twitter specifically has been used for a variety of research. These works have, for instance, analyzed climate change perception [40–42], assessed climate preferences [43], subjective wellbeing [44] and perceived flooding thresholds [45] across the US, predicted crime in Chicago (Illinois, US) [46], exposed gaps in the digital infrastructure of socially vulnerable communities [47] and identified increased Sinophobia during the Covid-19 pandemic [34]. A range of studies focuses in particular on examining temperature-dependent behavioral changes through Twitter data, suggesting connections between ambient temperature and climate change perception [41], assessing the remarkability of unusual temperatures [48] and exposing a link between altered mental wellbeing and exposure to unusually high temperatures [49].

This study contributes to the climate and conflict literature in two respects. First, we illuminate a hitherto unexamined impact channel in the field of climate-conflict research: The effect of temperature on online racism, finding evidence for a nonlinear relationship on the European level and for individual countries. Second, most studies based on Twitter data focus on English tweets. Here, we assemble and analyze about ten million tweets from six different European languages, adding a new layer to the analysis. Using Twitter data in combination with geographically distinct variables such as temperature requires the approximation of a tweet location. Only a very small number of tweets is geolocated due to the opt-in nature of this feature [45]. The data density for racist tweets is very low across Europe, making a study reliant on geolocated tweets unfeasible due to the statistical limitations. Instead, we here exploit the linguistic plurality of Europe and assign tweets to a location based on their language.

The remainder of the paper is structured as follows. Section 2 contains the Data and Methods, providing detailed information on the experimental design and statistical analysis. Section 3 presents the main results and robustness checks. Section 4 discusses the implications of the results in the context of previous research and against the backdrop of future warming and concludes the paper.

2. Data and Methods

We combine Twitter data from European countries spanning multiple climate zones with temperature data to assess the influence of temperature on the amount and acceptance of racist tweets. In this section, the experimental design and the statistical analysis are described.

2.1. Data

2.1.1. Languages

We consider tweets in Norwegian, Swedish, Danish, German, Italian and Greek. These six languages were chosen because they are mainly spoken in geographically confined areas and not widely used in other parts of the world which makes a location approximation through language feasible. The inclusion of further countries is hindered either by the fact that the respective language is internationally spoken or by low data availability. Moreover, the regions we consider cover the main variety of different climatic zones in Central Europe according to the Köppen–Geiger climate classification system [50]. At the same time the intra-country spatial climatic variability of each of these countries is limited.

2.1.2. Twitter data

For each language, we identify a set of racist, xenophobic and religiously discriminatory tweets (from here on referred to as racist tweets) from the years 2012–2018 using a simple bag-of-words approach: a set of key words is assembled in each language and tweets that contain any of these key words are added to the data set. More details on the words used and the assembly process can be found in the SI appendix section S1.1 (available online at stacks.iop.org/ERL/16/114001/mmedia) as well as in the SI appendix table 1.

The preprocessing workflow for the data is illustrated in figure 1. First, the data for each language are filtered to remove any duplicates. Second, we exclude tweets from users that only have an offensive username but do not necessarily post racist content.

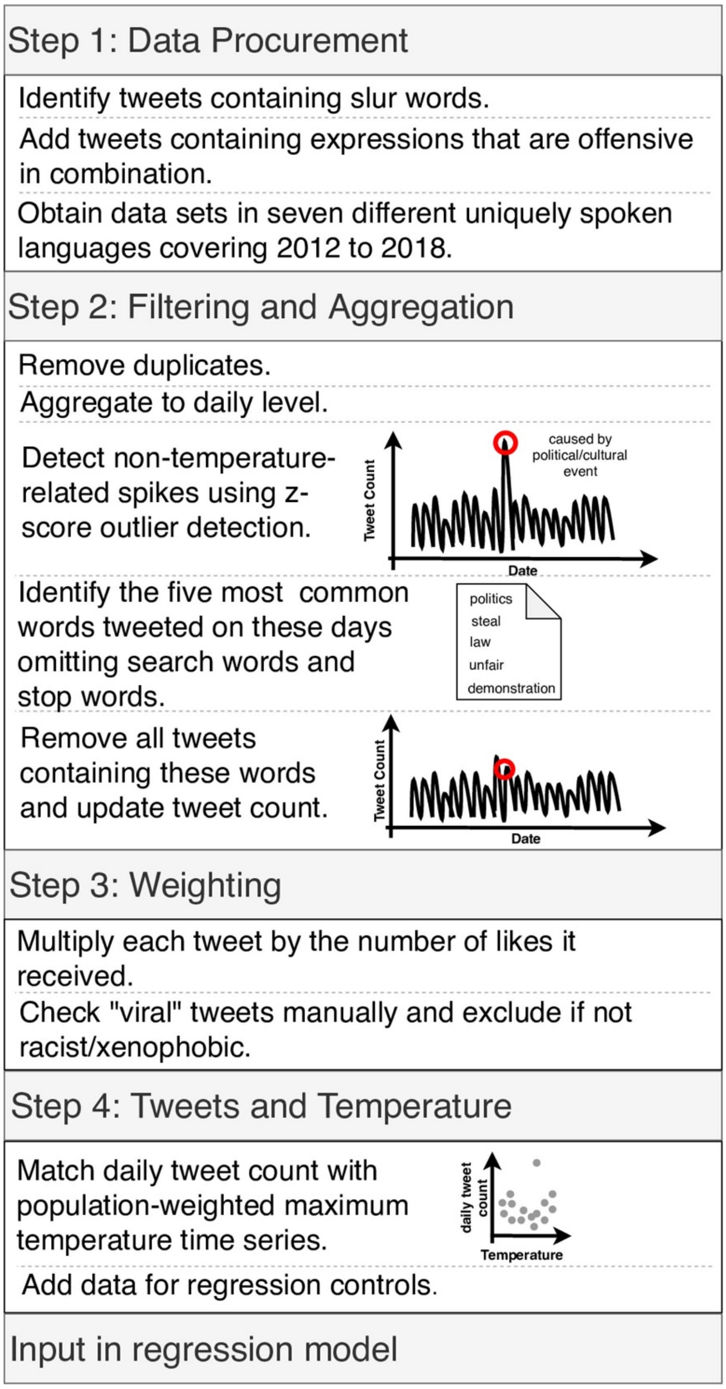

Figure 1. Data preprocessing workflow. Racist tweets are identified using a bag of words approach in six languages. They are filtered (duplicate removal, correction for non-temperature-related events) and aggregated to 24 h intervals. Next, each tweet is duplicated according to the number of likes it received, to additionally consider approval of racist content. Extreme outliers are checked manually for the presence of unrelated viral tweets. Lastly, the daily tweet count is combined with population-weighted daily average temperature data.

After this basic filtering, the data are aggregated to the daily level which roughly represents the rhythm at which users consume Twitter and experience weather. Furthermore, as social media usage is an element in everyday life, hot hours in the middle of the day could still be connected to aggressive behaviors in the evening when free time permits an increased social media activity. Tweets that contain multiple different slur words contribute multiple times to this daily tweet count as they usually contain offenses against multiple groups, worsening their impact. Tweets that were detected due to combinations of words only contribute once (see SI section S1.1).

Next, an outlier detection is performed in order to account for noise and temperature-independent incidents that cause spikes in racism (see SI section S1.2). After updating the tweet counts for all outliers, a common time series for the daily tweet count is created by adding the updated tweet counts for each day.

Each tweet is then multiplied by the number of likes it receives, where tweets that receive no likes are still counted as one. This process ensures that a more indirect form of racist behavior is captured as well: liking a racist tweet expresses agreement, which can be treated as a racist action itself as it amplifies the force and potentially the reach of the discrimination. The number of racist tweets and likes captures both the incidence of racist content and its indirect acceptance.

Some of the tweets detected with the bag-of-words approach might not be racist themselves but cite or discuss content that compromises the key words. This type of tweet might generate more likes than a genuinely racist tweet. To avoid distortions in our data sets through such mislabeling errors, tweets with an exceptional number of likes are assessed manually. That is, we define a threshold and check all tweets that have a like count above this threshold by hand. If these 'viral' tweets are not racist themselves, we exclude the day from the analysis. Overall, we analyze about ten million tweets.

2.1.3. Population-weighted climate data

The number of daily racist tweets and likes in each country c is then combined with a daily timeseries of population-weighted average temperature. Climate data on a 0.5° grid come from the ERA-5 reanalysis data set [51]. Population data, also on a 0.5° grid, are provided by ISIMIP [52] (see section S1.3–S1.5 in the SI appendix for detail).

2.2. Empirical strategy

Our empirical strategy uses exogenous variation in local weather to identify the effect of population-weighted daily average temperature on the daily number of racist tweets and likes. Key assumption for identification is that variation in temperature is random conditional on a set of fixed effects [9, 53, 54]. That is, we apply a fixed-effects panel regression model that exploits within region changes in temperature and the number of racist tweets and likes, thus eliminating many potential sources of omitted variable bias which distort inter-regional comparison and therefore strengthening the inference of causality in our findings [53, 55]. The independent variable is the number of racist tweets and likes $R_{\mathrm{c,d}}$ in country c at day d where tweets that have received no likes are still counted as one. In our main model, the dependent variable is population-weighted daily average temperature $T_{\mathrm{c,d}}$ in degrees Celsius.

We choose a semi-parametric approach that allows for nonlinear temperature effects [56–58]. The data are discretized into 3 °C bins covering a range from −10 °C to 35 °C, making it possible to conduct a primary analysis without having to specify a functional form or make more assumptions about the data. Other bin sizes were considered and are shown as controls (SI appendix, figure S1). The discretization is also sensible given the context of the study: An incremental difference in temperature is unlikely to introduce behavioral changes. Instead, it is more likely that different temperature ranges are perceived as desirable or undesirable. We introduce a dummy variable B_i for each bin i where

$$B_i(T_{\mathrm{d}}) = \begin{cases} 1 \text{ if } T_{\mathrm{d}} \in B_i \\ 0 \text{ else} \end{cases}.$$

In order to assess the percentage change in the number of racist tweets and likes the dependent variable is logged. We consider $\log(R_{\mathrm{c,d}}+1)$ to impute days with no racist or xenophobic tweets.

A series of control variables is included in the model to isolate the response of the number of racist tweets and likes to temperature. First, we control for daily precipitation P_{d}. As the literature suggests that the tweet pattern differs between weekends and weekdays [59], we further introduce a dummy W where:

$$W(T_{\mathrm{d}}) = \begin{cases} 1 \text{ if } T_{\mathrm{d}} \text{ is a weekend day} \\ 0 \text{ else} \end{cases}.$$

Moreover, we approximate the data by Chebyshev polynomials up to order 5 to flexibly control for trends and nonlinearities that operate on a lower frequency than the daily level [60–62] such as for example the development of Twitter users over time or the amount of derogatory content removed by Twitter itself which is fluctuating according to a study of the European Commission [63]. Chebyshev polynomials are defined recursively with $\mathrm{Ch}_0(d)=1$ and $\mathrm{Ch}_1(d)=d$, where d is the count of days ($d \in [0, 2492]$). All higher order polynomials can then be inferred using the formula: $\mathrm{Ch}_{j(d)} = 2\mathrm{dCh}_{j-1}(d) - \mathrm{Ch}_{j-2}(d), j \geqslant 2$. Our robustness checks (compare SI appendix figure S2) suggest that polynomials up to order 5 are sufficient to obtain robust results.

Finally, we include season fixed effects to control for seasonality (σ_{s}) and country fixed effects (μ_{c}) to account for unobserved, time-invariant differences between countries such as institutional and cultural differences.

The overall regression model thus reads as:

$$\log(R_{\mathrm{c,d}}+1) = \sum_{i=0}^{N_{\mathrm{b}}} \alpha_i B_i(T_{\mathrm{c,d}}) + \beta P_{\mathrm{c,d}} + \gamma W(T_{\mathrm{c,d}}) + \sum_{j=0}^{5} \delta_j Ch_{c,j}(d) + \mu_{\mathrm{c}} + \sigma_{\mathrm{s}} + \epsilon_{\mathrm{c,d}};$$

where N_{b} is the number of bins, α_i are the regression coefficients of interest and $\epsilon_{\mathrm{c,d}}$ is the stochastic error term. The coefficient α_i is a semi-elasticity that measures the marginal effect of an additional day in temperature bin B_i relative to the omitted bin. In all analyses in this study we omit the minimum bin, for the European panel regression this corresponds to the 5 °C–8 °C bin.

Apart from the main specification of the model detailed here we conduct a series of robustness checks, for example on alternate independent variables such as daily maximum temperature or heat stress measures. For more information please refer to the SI appendix section S1.6.

In addition to the European panel regression, we run individual regressions on country level. The regression model on country level reads as:

$$\log(R_\mathrm{d}+1) = \sum_{i=0}^{N_\mathrm{b}} \alpha_i B_i(T_\mathrm{d}) + \beta P_\mathrm{d} + \gamma W(T_\mathrm{d}) + \sum_{j=0}^{5} \delta_j Ch_j(d) + \sigma_\mathrm{s} + \epsilon_\mathrm{d}.$$

2.3. Temperature-racist-tweet response curve

As our regression results point to a quasi-quadratic response curve (see section 3), we use a quadratic fit p to parametrize the relationship between temperature and racist tweets. Only bins that contain at least 1.5% of the data are considered. We fit this quadratic, referred to as temperature-racist-tweet response curve hereafter, both at the country-level and for the whole panel as well as for all alternative model specifications we use as robustness checks (i.e. bin size, degree of Chebyshev polynomials, alternative heat stress measures, compare SI appendix, figures S1–S3). All fits yield parabolas with minima in the range between 5 °C and 11 °C, referred to as climate comfort zone from hereon. However, these bounds should not be interpreted as a hard limit but more as an indication because the response is discretized due to the binned approach. The quality of each fit is assessed using the R^2 score (SI appendix, table 2).

2.4. Projections

To assess how changes in temperature patterns under future warming could affect the number of racist tweets and likes within the next 30 years, we compare the percentage share of days colder and warmer than the climate comfort zone weighted by the strength of the temperature-racist-tweet response (denoted by x_cold and x_warm respectively). Let $\mathrm{d\_cool} = \{d | T_\mathrm{d} \leqslant 5\}$ and $\mathrm{d\_warm} = \{d | T_\mathrm{d} > 11\}$ be the number of days cooler and warmer than the climate comfort zone, respectively. We define:

$$x_\mathrm{cold} = \frac{\sum_{\mathrm{d}\in\mathrm{d\_cool}} p(T_\mathrm{d})}{\sum_\mathrm{d} p(T_\mathrm{d})}$$

$$x_\mathrm{warm} = \frac{\sum_{\mathrm{d}\in\mathrm{d\_warm}} p(T_\mathrm{d})}{\sum_\mathrm{d} p(T_\mathrm{d})}$$

where p refers to the European temperature-racist-tweet response curve (compare section 2.3). We compute x_cold and x_warm for the time period of 2012–2018 and for 2044–2050 for shared socioeconomic pathways (SSPs) 1–26 and 5–85 and then analyze the percentage change between the two periods. For the extrapolation to a warmer climate 36 European countries are included, assuming their temperature-racist-tweet response is represented in the European panel through the contribution of countries lying in similar climatic zones.

3. Results

3.1. The European temperature-racist-tweet response

The results of the panel regression show a quasi-quadratic relationship between daily average temperature and the number of racist tweets and likes (figure 2, black dots). Levels of racist tweets are comparatively low in the two bins encompassing 5 °C–11 °C and then sharply increase outside of this temperature range where there is sufficient data coverage (figure 2, opacity). For cold days the increase amounts to around 20%, for warm days it reaches almost 60%. We parametrize this relationship using a quadratic fit (see section 2.2). The minimum of the resulting curve, referred to as temperature-racist-tweet response function from hereon (red curve in figure 2), falls in the 5 °C–11 °C range which we define as the climate comfort zone (compare section 2.3).

Comparing the histogram of the daily average temperature to the shape of the temperature-racist-tweet response function, we see that commonly experienced temperatures coincide with low levels of racist tweets and likes. The rarer a temperature is, the stronger the relative increase of racist tweets and likes. The mean daily average temperature over the whole time period (2012–2018) falls within the climate comfort zone (blue line, figure 2). This inverse-proportional relationship between the frequency of the temperature and the percentage change in racist tweets and likes indicates that the temperature-response of racist tweets and likes may be determined by the climate we are used to.

3.2. European climate comfort zone persists on the country level

In a next step, we conduct analyses at the country level. This serves the double purpose of investigating the robustness of the climate comfort zone on the one hand and further assessing the relationship between the local temperature distribution and the country-specific temperature-racist-tweet response on the other.

Norway and Sweden are the highest latitude countries included, representing a cooler, boreal climate. In comparison, Denmark and Germany/Austria have a more temperate climate. Italy and Greece are the most Southern countries included and represent warmer, Mediterranean temperatures. The binned-regression model is adapted to the country level while

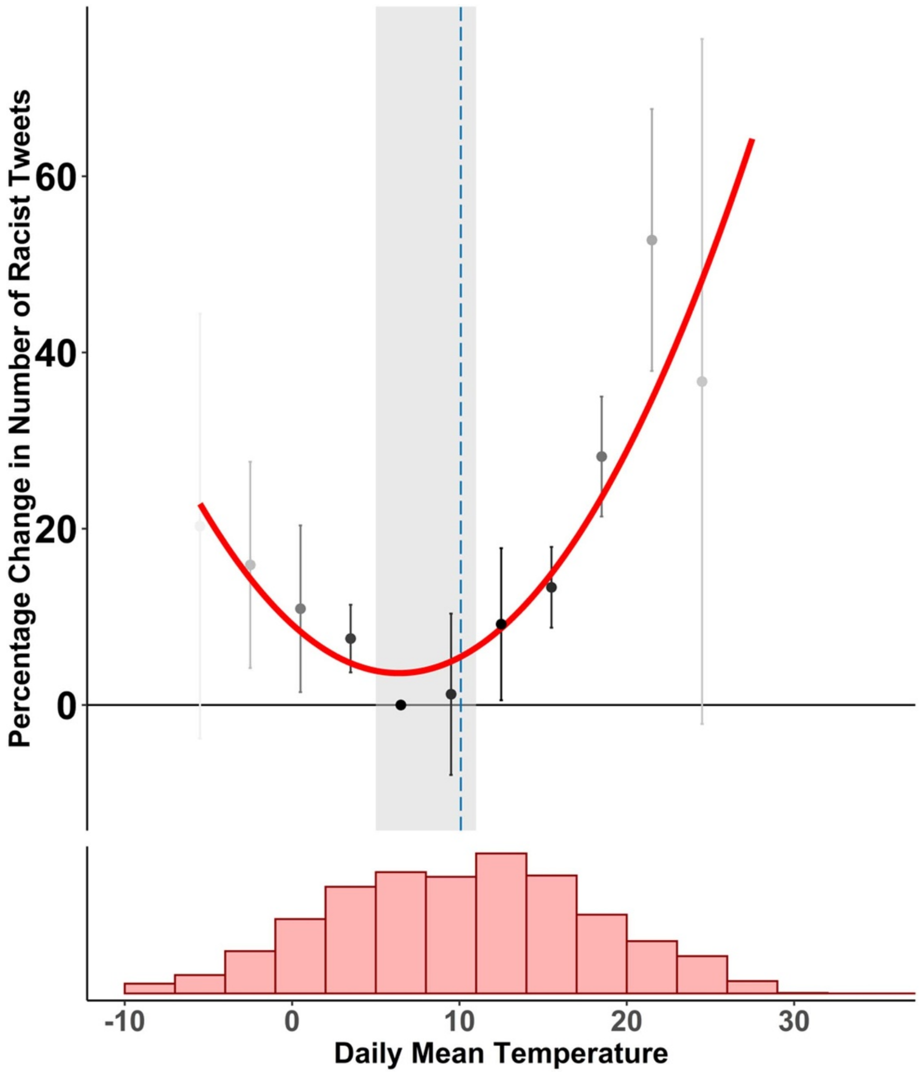

Figure 2. The number of racist tweets and likes has a nonlinear temperature response with low levels between 5 °C and 11 °C. The results of the European fixed-effects panel-regression model describe the relationship between population-weighted daily average temperature (x-axis, 3 °C bins) and the number of racist tweets and likes (y-axis). The data follow approximately a quadratic shape (red curve) with a minimum in the range between 5 °C and 11 °C (grey area) and strong increases outside of this region. The histogram of the daily average temperature shows that commonly experienced temperatures coincide with low levels of racist tweets whereas rarely experienced temperatures are associated with steep increases. The average temperature over the period considered (blue line) falls within the climate comfort zone.

maintaining the main parameters and controls from the panel approach (compare section 2.2).

For all countries but Greece a quasi-quadratic nonlinear response between daily average temperature and the number of racist tweets and likes can be observed (figure 3) which is similar in shape to the European temperature-racist-tweet response where there is data coverage. Greece experiences so few days with daily average temperatures below 5 °C that the response is here not quadratic but a near-linear increase of racist tweets and likes with temperature. All country-specific temperature-racist-tweet response functions have their minima in the climate comfort zone, suggesting that this range is common across different European regions and climates. However, the magnitude of the cold and warm responses differs from country to country. The countries that experience colder temperatures have a pronounced cold response with the percentage increase peaking at around 90% for Norway and around 70% for Sweden whereas their warm responses only reach around 30% and 40% respectively. Denmark has a more pronounced response to warmer temperatures with increases reaching around 60% whereas the peak for cooler temperatures lies just below 40%. Germany/Austria experiences smaller increases in general with the cold response reaching around 30% and the warm response almost 20%. Italy and Greece have no cold response as there are barely any cool days. The response to hot temperatures however is especially for Italy pronounced with an increase of up to 80%. The increase for Greece peaks around 30%–40%.

Interpreting these results against the backdrop of the regional temperature distributions, we observe that the placement of the temperature-racist-tweet response curve along the temperature axis coincides

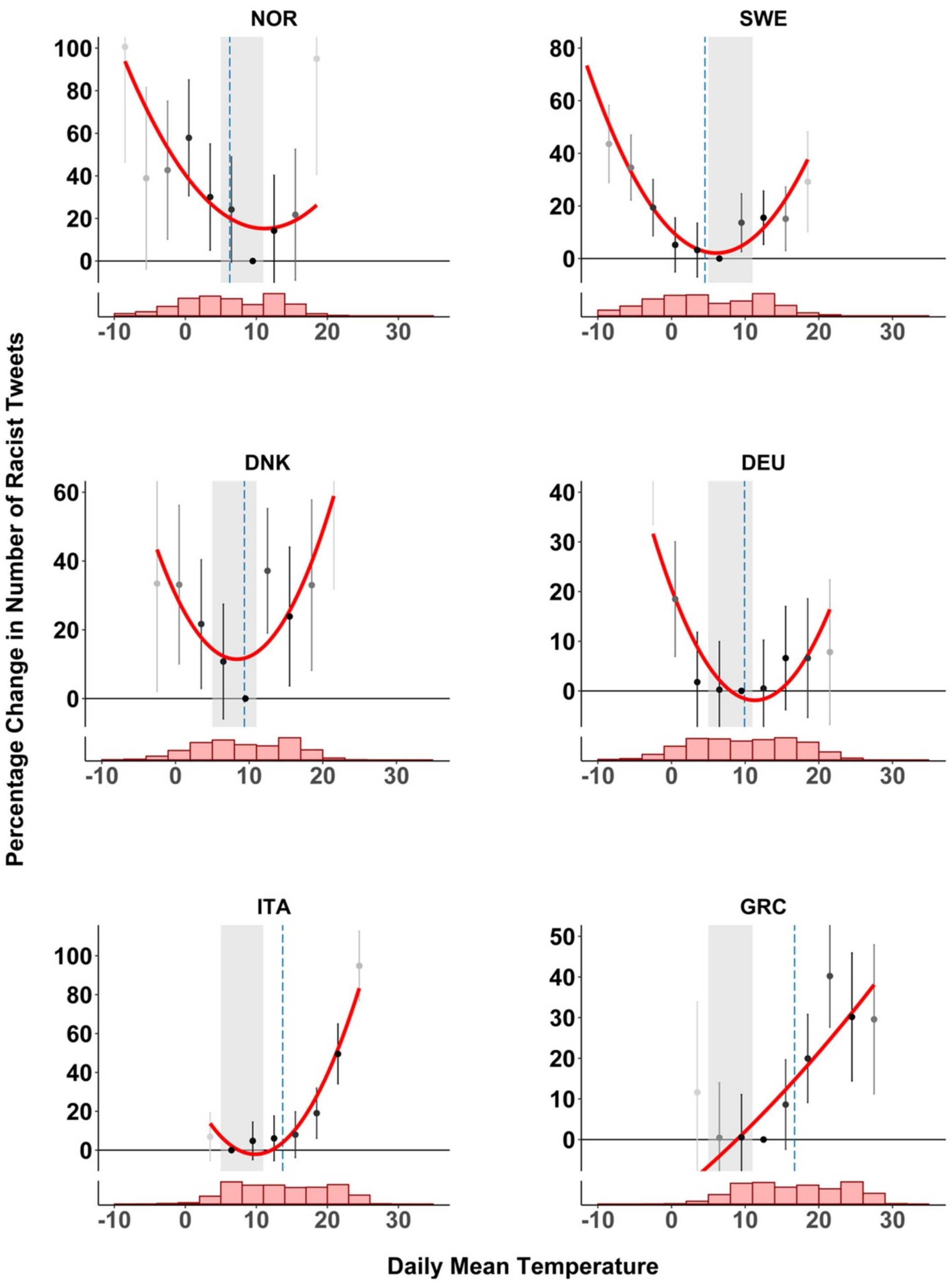

Figure 3. Minima of country-specific temperature-racist-tweet response functions match the European climate comfort zone. Black markers show the results of the binned fixed-effects regression at the country level for the relationship between population-weighted daily average temperature (x-axis, 3 °C bins) and the number of racist tweets and likes. For each country, the data show a nonlinear relationship with low values between 5 °C and 11 °C further supporting the presence of a European climate comfort zone. The nonlinear increases can be described by the country-specific temperature-racist-tweet response (red curves) where there is data coverage (opacity of the data points). For cooler and temperate countries, the average temperature across the whole observation period (blue line) falls within the climate comfort zone, for warm countries there is a clear deviation. Similarly, the temperature histograms align well with the placement of the curve for cool and temperature countries as opposed to a shift for warmer countries.

for the cooler and temperate climates with the histogram of the daily average temperature. As on the European level, frequently experienced temperatures are associated with low levels of racist tweets and likes whereas less frequent temperatures correspond to stronger increases. For Norway, Denmark and Germany/Austria the temperature average across the whole timeframe falls within the climate comfort

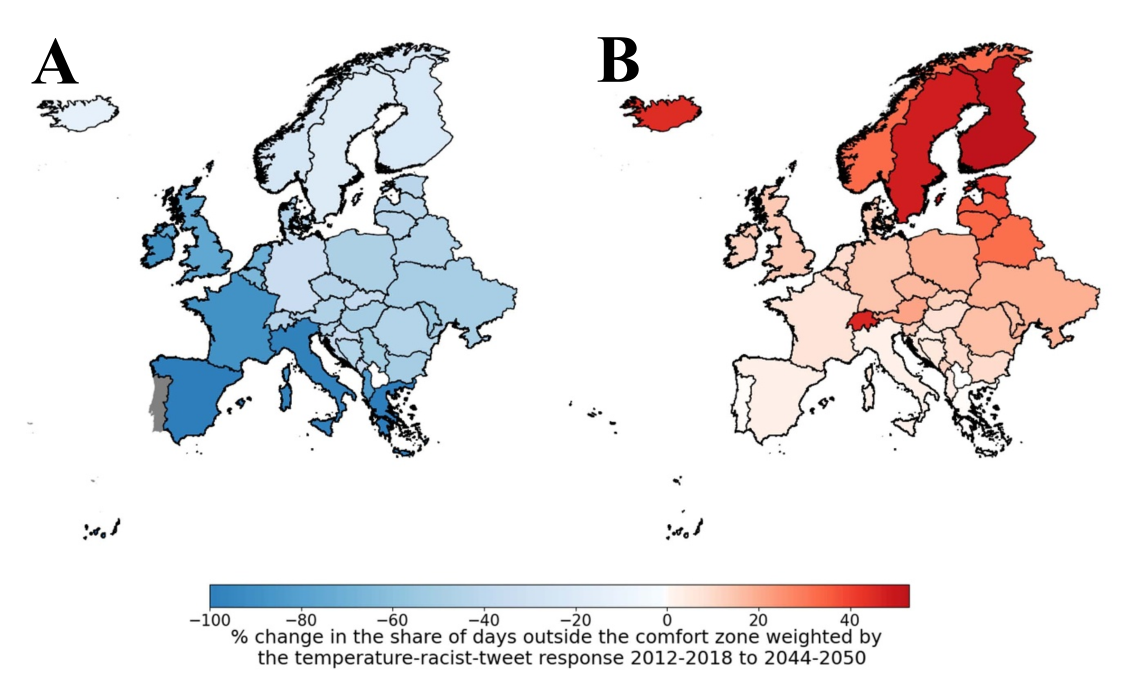

Figure 4. Percentage change in the share of days colder (panel (A)) and warmer (panel (B)) than the climate comfort zone in 2044–2050 compared to 2012–2018, weighted by the strength of the temperature-racist-tweet response. The measure reflects the cumulative combined effect of changes in the share of days colder and warmer than the climate comfort zone and the strength of the temperature-racist-tweet response. Temperature projections correspond to a business-as-usual emissions scenario (SSP 5–85). For temperatures below the climate comfort zone a decrease can be observed across all of Europe with the impact vanishing completely for most of Southern and Western Europe. The share of response-curve-weighted days warmer than the climate comfort zone increases across all of Europe with particularly pronounced rises in Northern and Eastern Europe.

zone, for Sweden it lies just below it (deviation of less than 0.5 °C). This could suggest that the regional temperature distribution is one of the determining factors in the relationship between temperature and racist tweets. However, for the warmer countries (Italy and Greece) we see a mismatch between the numbers of racist tweets and likes and the temperature distribution. Even though both countries frequently experience warmer temperatures, the minima of the temperature-racist-tweet response curves lie within the European climate comfort zone. For Italy the average temperature over the whole observation period lies around 3 °C above the climate comfort zone, for Greece the deviation amounts to more than 5 °C. This might suggest limits to adaptation, i.e. even though high temperatures are frequently experienced, the climate comfort zone where the number of racist tweets and likes is lowest is not shifted accordingly.

3.3. Extrapolation to a warmer climate

With temperature distributions shifting due to anthropogenic greenhouse gas emissions, the number of days inside and outside the climate comfort zone is likely to change over the next few decades. Abstracting from other factors that might lead to changes in social media usage in general and the occurrence of cyber racism specifically, we here focus on the temperature dependence alone and assess how the number of racist tweets and likes might change due to these projected shifts in temperature distributions, especially if there is no or only limited temperature adaptation. Using the recently released temperature projections from ten Global Circulation Models of the Coupled Model Intercomparison Project phase-6 (CMIP-6) (compare SI appendix, table 3), we assess the share of days warmer or colder than the climate comfort zone in 2044–2050 compared to 2012–2018. We thereby take the strength of the deviation from the comfort zone into account, weighting it in accordance with the previously identified temperature-racist-tweet response function (referred to as response-curve-weighting hereafter, see section 2.3). We distinguish between the two most extreme emissions scenarios, i.e. SSPs 1–26 and 5–85, corresponding to an ambitious and a business-as-usual climate change mitigation scenario, respectively [64].

As multiple European climatic zones are included in the panel, the resulting curve is likely to hold for other European regions as well. Consequently, we extend this analysis and assess future changes in temperature distributions for 36 European countries (SI appendix, table 4).

For SSP 5–85, the response-curve-weighted number of days colder than the climate comfort zone decreases across all of Europe from 2012–2018 to 2044–2050 (figure 4(A)). In Southern and Western Europe, the percentage reduction is close to 100%: days colder than 5 °C cease to occur almost entirely under these projections. Portugal was excluded from the analysis of cold days as it had no days colder than the climate comfort zone in the reference period.

By contrast, the response-curve-weighted number of days warmer than the climate comfort zone in 2044–2050 increases in all European countries compared to 2012–2018 (figure 4(B)). We find particularly strong increases in Northern and Eastern Europe as well as Switzerland. In Finland and Sweden, the increase amounts to around 50%, followed by Iceland, Estonia and Switzerland (∼45%). Assuming a more ambitious climate change mitigation (SSP 1–26), we find consistent, albeit less pronounced trends with the response-curve-weighted number of warm days increasing by around 25% (compare SI appendix figure S4). For the SSP 1–26 scenario Iceland is an exception as the number of response-curve-weighted warm days for Iceland significantly decreases (−57%). The percentage changes for each country are shown in SI appendix, table 4.

For some countries, the increase in response-curve-weighted days warmer than the climate comfort zone for SSP 5–85 is stronger than the decrease in weighted days colder than the climate comfort zone. The combined effect under SSP 5–85 is found to be strongest in Iceland (−13% cold, +45% warm) followed by Finland (−22% cold, +52% warm), Sweden (−20% cold, +48% warm) and Norway (−25% cold, +33% warm). These countries might therefore experience increases in the occurrence and acceptance of racist online-content due to climate change, assuming that all other influencing factors are held constant.

4. Discussion and Conclusions

Consistent with previous findings on the relationship between temperature and social conflicts in the physical world, we here show that the occurrence and acceptance of racist and xenophobic tweets in the virtual world, i.e. on the social media platform Twitter, is nonlinearly influenced by temperature. Our results indicate that the number of racist tweets and likes is lowest for population-weighted daily average temperatures between 5 °C and 11 °C, independent of the climatic zone within which the Twitter users are located. This range, outside of which racist content increases steeply, is identified at both the European and the national level.

Instead of relying on the limited number of geolocated tweets, we are able to substantially increase the amount of data available by exploiting the linguistic plurality of Europe. By approximating the location of the user through the language in which they tweet, we avoid relying on the small subset of tweets which use the opt-in geolocation function[6]. However, approximating location via language might introduce some biases. According to the UN in 2019 the share of the population living abroad is between 2.05% (Sweden) and 9.19% (Greece; compare SI appendix, table 5) for the countries included in this study. This share of the population might tweet in their native language without experiencing the temperatures assigned to the location of that language. However, as these emigrants are scattered across multiple countries, it is unlikely that we introduce enough tweets from the same foreign country to bias the temperature distribution towards it.

In comparison to heat-stress measures based on human physiology, where temperatures between 18 °C and 23 °C are interpreted as comfortable [65], the here identified climate comfort zone of 5 °C–11 °C is low. However, due to its spatial and temporal aggregation the temperature variable used here does not reflect the exact ambient temperature experienced by each Twitter user, but rather acts as an indicator for it. Given that daily average temperature is computed over a 24 h interval, nighttime temperatures are included in the measure, introducing a bias towards daily average temperatures colder than the temperatures typically experienced in a day. Furthermore, the identified climate comfort zone is comparatively close to the annual average temperature of the current human climate niche which lies at around 13 °C [66] and characterizes the subset of Earth's available climates that humans have succeeded in for more than six centuries.

Given that the climate comfort zone holds for all countries considered—even the hotter Southern European countries that frequently experience temperature warmer than that—we assume that it may also hold under future warming. Further research on temperature adaptation is necessary to robustly test this hypothesis. Moore *et al* [48] found that even though the remarkability of unusual temperatures declines over time at continued exposure, the sentiment score does not improve, indicating a lack of adaptation. Assuming the climate comfort zone is indeed constant under future warming, we assessed the change in share of response-curve-weighted days outside of the climate comfort zone under SSP 5–85. It decreases on average for days colder than the climate comfort zone and increases on average for days warmer than the climate comfort zone. These findings also hold for an SSP 1–26 scenario. For some European countries the increase in warm days outweighs the decrease in cold days, but even for those where the 'net effect' is low, the considerable change in the seasonal distribution of days outside of the climate comfort zone may be problematic. Overall, our results suggest that under future warming, the occurrence and acceptance of racist content online could increase. These estimates abstract from all other influencing factors. For instance, it is impossible to predict how social media will be used in three decades, which will heavily influence the future patterns of

[6] Using geolocation data alone does not allow for a comprehensive analysis.

online hate speech. Furthermore the development of other socioeconomic factors will affect the relationship between climate and conflict [67].

In conclusion, our research illuminates cyber racism and xenophobia as a new impact channel through which temperature can affect societal conflict. However, large uncertainties remain about the causal relationship between temperature and the amount and acceptance of racist and xenophobic content on Twitter and interdisciplinary, contextual research is needed to understand the mechanisms leading to this observation.

Declaration of interests

The authors declare no competing interests.

Data sharing

In compliance with Twitter terms of service restrictions and due to privacy concerns, the Twitter data will not be shared in a public repository.

All historical climate data used originates from the ERA-5 re-analysis data set which can be downloaded from the Climate Data Store [https://confluence.ecmwf.int/display/CKB/How+to+download+ERA5]. The future daily average temperature data for each gridcell was obtained by averaging over an ensemble of ten bias-corrected CMIP-6 climate models. A detailed overview of models and their sources is listed in the SI appendix, table 3. The assembled climate data set used for projections can be requested via email to the corresponding author.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

General: We thank Kelsey Barton-Henry, Anja Bruhn, Daniel Drake, Martinus Førde, Jevgenij Gamper, Anastasis Giannousakis, Anne Gossing, Jennifer Hack, Patryk Kubiczek, Robin Middelanis, Clara Palmisano, Lennart Quante and Jasmin Wrede for their help with generating the sets of search terms in different languages. We thank Frederik Wolf for his advice.

Funding: We gratefully acknowledge the funding from the Volkswagen Foundation.

Author contributions: A S processed the climate and Twitter data. A S and L W designed the models. A S, L W, A L and M K analysed the results. A S and L W wrote the manuscript.

ORCID iDs

A Stechemesser https://orcid.org/0000-0002-8306-1735
L Wenz https://orcid.org/0000-0002-8500-1568
M Kotz https://orcid.org/0000-0003-2564-5043
A Levermann https://orcid.org/0000-0003-4432-4704

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