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Perceived Temperature, Trust and Civil Unrest in Africa

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Abstract:

This paper documents a significant effect of short-term temperature fluctuations on attitudes towards institutions and on civil unrest in Africa. Combining attitudinal survey and climate data, we calculate temperature as perceived by respondents via an algorithm that combines different meteorological variables. The results show that daily temperature anomalies at the location of interview increase self-reported mistrust in government and intentions to vote for opposition parties. Effects are particularly strong in poor countries where temperature anomalies also increase self-reported intentions to protest. Accordingly, we find that temperature anomalies also increase incidences of protests and riots. Evidence suggests that effects are not driven by changes in agricultural incomes.

Key words: Climate, Trust, Conflict

JEL Classifications: D74, Q54, N57

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1 Introduction

The links between climate and conflict are well documented. In numerous settings, hotter or drier climate has been associated with higher incidences of conflict (see Burke et al., 2015; for an overview). Much of the literature has focused on income as a pathway of impact where weather fluctuations lead to changes in income, which, in turn, affect conflict (see Dell et al., 2014; for a general discussion). However, there is also a growing body of evidence pointing to a direct physiological, psychological effect of temperature on violence. At higher temperatures, for instance, individuals have been found to act and think more aggressively (see Anderson et al., 2000; for a psychological overview). One biological process underpinning the link between heat and violence is the human body's serotonin uptake, which regulates impulse control and attitudes and also responds to temperature (Pietrini et al., 2000; Tiihonen et al., 1997, 2017). Nevertheless, there is still little evidence on the effect of temperature on attitudes towards institutions as a potential mechanism of impact.

This paper estimates the effect of temperature as perceived by the human body on self-reported mistrust in government, voting intentions and on incidences of civil unrest in Africa. Matching individual-level, Africa-wide survey data with high-resolution information on daily climatic events, we relate temperature as experienced by the respondent on the day of the interview to self-reported attitudes. We start by focusing on trust, which is closely linked to conflict (see Kramer, 1999 for an overview and Acemoglu and Wolitzky, 2014; Rohner et al., 2013; for examples). Using hypothetical questions on voting and protesting, we further ask whether temperature also affects intentions to act. Finally, we investigate incidences of protest and riots for the entire African continent at the sub-national cell level.

For our first set of findings, we exploit plausibly exogenous day-to-day differences from the local long term mean (also defined as anomalies) to identify the effect of temperature on self-reported mistrust in government and intentions to vote and to protest. We measure temperature as experienced by respondents via an algorithm that maps four meteorological variables affecting the body's heat perception (air temperature, humidity, wind speed and solar radiation) to an index for perceived temperature. We draw data for each of these four meteorological variables from the ECMWF2-ERA5 reanalysis and match it to the sixth round of the Afrobarometer, a representative attitudinal survey covering around 50,000 respondents in 33 countries across Africa. Combining respondents' exact geographical coordinates and the date of their interview with the algorithm, we calculate perceived temperature on the day and precise location of the interview. Across six different questions approximating trust in government, the estimates show that a 1°C deviation from the long-term mean increases mistrust in government by almost 1 percentage point. Effects are particularly strong if the respondent and the head of state are from different ethnicities and if the respondent's ethnicity was subjected to historical slave trade. Using perceived temperature during the two days before or after the interview gives precisely estimated effects of zero. As a placebo, we find precisely estimated parameters of zero for past experiences of respondents. Of the algorithm's four components, humidity has the strongest effect on mistrust.

We also find that perceived temperature anomalies affect self-reported intentions to act. Comparing self-reported voting intentions to the party of the current head of state, we find that a positive 1°C perceived temperature anomaly increases the probability of respondents intending to vote for a different party than the president by around 0.7 percentage points. Crucially, for countries with high incidences of poverty where dissatisfaction and grievances are particularly likely, we find that a positive 1°C perceived temperature anomaly increases the probability of a respondent reporting to intend to protest by 0.8 percentage points.

For our second set of findings, we estimate the effect of perceived temperature on incidences of protests and riots by combining climate data with information from the Armed Conflict Location and Event Data (ACLED) Project for the the whole of Africa. Using the map provided by Harari and La Ferrara (2018), we divide the continent into 2,757 cells of size 1×1 degree latitude and longitude (approximately 110km at the equator) and create a monthly panel for the years 2009 to 2018. We find that a 1°C positive perceived temperature anomaly increases the within-cell incidence of riots and protests by around 0.3 percentage points. By contrast, we find no effect on incidences of conflict motivated by strategic considerations. As before, effects are particularly strong for poor and ethnically diverse cells.

Four separate pieces of evidence all suggest that the effect of perceived temperature on protests and riots operates independently of fluctuations in agricultural incomes. First, we find no effect for the three leads and lags for month m. Climatic fluctuations, however, typically take more than a month to change agricultural output (Parvin et al., 2005). Second, we identify the growing season for the major crop cultivated in each of the 2,757 cells, when crops are particularly sensitive to climatic fluctuations. We find that the effect of perceived temperature does not vary with where month m falls within the cell-specific growing calendar. Third, of the algorithm's four components humidity shows the strongest effect on protests and riots. Whilst human heat perception reacts strongly to humidity (Tsutsumi et al., 2007; Alahmer et al., 2012), research shows a much smaller effect on plant growth (Zhao et al., 2005). Finally, when we regress annual agricultural gross value added (GVA) per worker on perceived temperature we find only very small estimates which are statistically indistinguishable from zero.

Evidence also suggests that the effect of perceived temperature highlighted in this paper complements (rather than rivals) the effect on conflict resulting from changes in agricultural incomes highlighted by, for instance, Harari and La Ferrara (2018). For each cell and month, we calculate the average temperature for all months in the previous year falling inside of the cell-specific growing season, which is a key determinant of harvests and thus of agricultural incomes. Within the same regression, the parameter estimate for this average temperature is comparable in magnitude to the effect of perceived temperature in month m. By contrast, the effect of the average temperature for months in the previous year falling outside of the cell-specific growing season is close to zero, which tallies Harari and La Ferrara (2018)'s findings. Taken together, these results suggest that the effect of temperature is twofold: higher temperatures affect conflict by decreasing agricultural incomes and also via a more direct, short-term effect.

By highlighting attitudes towards institutions as a novel mechanism through which temperature affects protests and riots, this paper contributes to the literature on climate and conflict. A large body of work highlights how climatic variables can affect conflict by changing incomes (Burke et al., 2009; Brückner and Ciccone, 2011; O'Loughlin et al., 2012; Dube and Vargas, 2013; Jia, 2014; Harari and La Ferrara, 2018). However, there is increasing evidence that the weather can also have an effect on conflict that does not operate via income (Sarsons, 2015; Baysan et al., 2019). Other studies have considered short term variations in the climate that are too short to cause significant changes in income (Jacob et al., 2007; Card and Dahl, 2011; Larrick et al., 2011; Ranson, 2014). By highlighting how attitudes are influenced by temperature, our paper proposes a new channel of impact for these effects. Moreover, our analysis uses data from the whole of Africa and leverages quasi-experimental daily fluctuations in the weather to identify an effect on attitudes and is thus similar in approach to experimental studies on temperature and behaviour (Vrij et al., 1994; Anderson et al., 2000; Almas et al., 2019).

The results presented here may also be of interest to the fast growing body of work on the determinants and consequences of collective action and protests (such as Steinert-Threlkeld et al., 2015; Qin et al., 2017; Acemoglu et al., 2017; Manacorda and Tesei, 2020; Enikolopov et al., 2020).

By linking climatic events to attitudes, this paper also speaks to the economic literature on trust, which has been seen as beneficial for the economy (Knack and Keefer, 1997; Fafchamps, 2006; Algan and Cahuc, 2010; Tabellini, 2010). Whilst many studies have pointed out the manifold determinants of trust, such as slave trade (Nunn and Wantchekon, 2011), football (Depetris-Chauvin et al., 2020), internet access (Guriev et al., 2019), social norms (Sliwka, 2007), societal structure (Moscona et al., 2017), historical residue (Fisman and Khanna, 1999), racial/ethnic cleavages (Alesina and La Ferrara, 2002), the role of climate has remained relatively under-explored. Attitudes and trust in particular have been shown to be closely linked with conflict (Bellows and Miguel, 2009) and civil unrest (Passarelli and Tabellini, 2017).

This paper is structured as follows: in the next section we present our datasources, measurements and summary statistics. Section 3 estimates the effect of perceived temperature on trust, voting intentions and intentions to protest. Section 4 estimates the effect of perceived temperature on incidences of protests and riots. Section 5 concludes.

2 Data and Conceptual Framework

2.1 Data and Measurements

The analysis combines data on climate, self-reported attitudes, civil unrest and topography from four independent sources.

i) Data on meteorological variables: Meteorological data are taken from the ECMWF2-ERA5 reanalysis, which contains high resolution climatic data generated from reanalyses of historic data using the Integrated Forecasting System (IFS) Cy41r2 model from 1950.[1] These data benefited from more than a decade of advances in meteorological research (Hersbach et al., 2020) and supersede the ECMWF ERA-Interim data used by Harari and La Ferrara (2018). To calculate our heat index, we employ data on surface air temperature (in °C), surface net solar radiation (in J/m^2), wind speed at 10 metres above the surface (in m/s) and surface dewpoint temperature (in °C), which we use to calculate humidity. For the individual-level analysis we use meteorological data measured on the day of interview. For the sub-national cell-level analysis we use monthly averages of meteorological data. All meteorological variables are recorded at 12noon local time. See appendix B for more details.

ii) Data on attitudes: Information on self-reported trust in government and intentions to vote and to protest is based on the sixth round of the Afrobarometer, which was conducted in 36 countries throughout Africa from March 2014 to November 2015. The survey covers approximately 54,000 individuals and is nationally representative of about 76 percent of the population across most of north, south and west of the continent. We drop the three island states of Cape Verde, Mauritius and Sao Tome and Principe. Upon request, the Afrobarometer also provides the geographical coordinates of respondents.

iii) Data on civil unrest: We measure civil unrest as incidences of either i) protests or ii) riots. Data are drawn from the Armed Conflict Location and Event Data Project (ACLED), which collects information on all reported political violence and protest events

[1] The IFS Cy41r2 model has been shown to give the most precise estimates for a range of climate variables. The data is available at `https://cds.climate.copernicus.eu`.

for Africa and other continents.[2] For each event, ACLED reports the date, actors involved, fatalities and modalities along with the exact geographical coordinates. Our outcome variables are i) protests, defined as *a public demonstration in which the participants do not engage in violence, though violence may be used against them* and ii) riots, defined as *violent events where demonstrators or mobs engage in disruptive acts*. We focus on the years 2009 to 2018.

iv) Topography: We combine the geographical locations of climatic events, Afrobarometer respondents and incidences of civil unrest using the geographical grid provided by Harari and La Ferrara (2018). This map divides the African continent into 2,757 quadrangular cells of size 1×1 degree latitude and longitude (approximately 110km at the equator)—see map in appendix A. For each cell, we also calculate long run averages for each month, which we use to calculate daily and monthly anomalies.

For each of the 2,757 cells, we also identify the major crop cultivated and calculate its growing season combining two data sources. We use data from the International Food Policy Research Institute (IFPRI) (Anderson et al., 2014) to identify each cell's major crop.[3] Crop-specific growing seasons are drawn from geo-referenced data on planting and harvesting dates from the Nelson crop calendar database, which includes data for 19 major crops across several countries worldwide (Sacks et al., 2010); see appendix B for a more detailed description.[4]

2.2 Heat Index for perceived temperature

The human body perceives a feeling of heat when its core temperature rises above 37°C. Temperature regulation occurs by a combination of perspiration and vasodilatation. The effectiveness of this process—and hence perceived temperature—depends on four environmental factors: air temperature, air humidity and sun exposure decrease cooling whereas airflow increases it (Steadman, 1984) .

One of the most widely used measures for perceived temperature (Steadman, 1994) combines four meteorological variables—temperature, humidity, wind and solar radiation—into a single index. This index denotes the equivalent temperature that the human body would perceive under a fixed set of climatic conditions (i.e. if dew-point temperature were 14.0°C). In simple terms, the index denotes the temperature as one would "feel" it. Steadman's index is the basis for a variety of heat indices provided by reputable institutions, such as, for instance, the National Oceanic and Atmospheric Administration (NOAA), the U.S. National

[2] The data are freely available under `https://acleddata.com/`.

[3] The data are freely available at `https://www.ifpri.org/`.

[4] The data are freely available at `https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/index.php`.

Weather Service[5] and the Australian Bureau of Meteorology.[6]

Steadman (1994) sets out different algorithms that translate any combination of the four aforementioned meteorological variables into a single index. The most comprehensive version, which accounts of outside weather conditions, models temperature as perceived by the human body, also defined as perceived temperature, as

$$heat\ index = T + F \tag{1}$$

where T denotes air temperature (measured in °C). The variable F, which we call the *feel factor*, accounts for the fact that temperature as perceived by the human body does not only depend on air temperature, T, but also on humidity, wind and solar radiation. The heat index deviates from air temperature as follows

$$F = 3.48 \times P_a - 0.7 \times ws + 0.7\frac{Q}{ws + 10} - 4.25 \tag{2}$$

where P_a is water vapour pressure (a measure of humidity, measured in hPa), ws is wind speed (measured in m/s) and Q is net solar radiation absorbed per unit area of body surface (measured in $\frac{w}{m^2}$). Humidity, more than any of the other variables in F, has been identified as particularly important in determining how temperature is perceived or felt by individuals (see Tsutsumi et al., 2007; Alahmer et al., 2012; for instance).

We include both temperature (T) and the feel factor (F) as separate covariates in our main regressions. To investigate the relative importance of the four components of the heat index, we also include all four (air temperature, humidity, wind and solar radiation) as separate regressors.

2.3 Measurements and summary statistics

Heat index: The distributions of air temperature and the heat index in equation 1 are reported in figures 1a and 1b. The combination of humidity, wind and solar radiation captured by the feel factor leads the perceived temperature to exceed air temperature by around 5°C. This holds for both the Afrobarometer sample (from 2014 to 2015 in panel a) and the ACLED sample (from 2009 to 2018 in panel b). A possible reason for the heat index exceeding air temperature is that we measure all climatic events at 12noon when solar radiation is the strongest. This is exacerbated by the fact that much of Africa lies relatively

[5]See for instance `https://www.weather.gov/oun/safety-summer-heatindex` accessed May 2020.
[6]For instance `https://www.wpc.ncep.noaa.gov/heat_index/details_hi.html` and `http://www.bom.gov.au/info/thermal_stress/` accessed May 2020.

close to the equator and that the effect of humidity on perceived temperature is particularly strong at high temperatures.

Trust, voting intentions and intentions to protest: We use six questions to approximate trust in government. These inquire whether the respondent i) trusts the parliament, ii) trusts the president or equivalent highest office of state, iii) believes politicians are out for themselves, iv) believes that the president should decide everything, v) believes there should be more than one party, and vi) believes that president should be bound by laws. See appendix C for a detailed descriptions of how the variables are created.

Average levels of trust are reported in figure 1c. Overall, trust in government is relatively low. Just under half of respondents report not to trust the parliament or the president of their own country. Moreover, around three quarters believe that politicians are "out for themselves", that the president should not do as he or she pleases and that the president should obey the laws. A similar proportion disapproves of one party rule.

To measure voting intentions, we use the hypothetical scenario in the Afrobarometer, which asks respondent which party they would vote for if elections were held the day after the interview. We define a dummy variable taking the value 1 if the party selected by the respondent does not match the party to which the current president is affiliated. Figure 1c shows that around 65 percent would vote against the current president. See appendix C for more detail.

We measure intentions to protest via a hypothetical scenario inquiring whether the respondent ever participated or would participate in a demonstration or protest march if they were dissatisfied with the government. Only a relatively small percentage, 9 percent, ever participated in a protest. We drop these individuals and define a dummy taking the value 1 if the respondent states that they would participate in a demonstration or protest march if they had the chance. As figure 1c shows, 37 percent would. See appendix C for more detail.

Protests and riots: Summary statistics for incidences of civil unrest, defined as either protests or riots, are reported in figure 1d. For the whole of Africa in the years 2009 to 2018, ACLED report a total of 28,762 protests and 16,080 riots. This corresponds to around 0.087 protests and 0.049 riots per cell per month In total, 47 percent of cells experienced at least one protest or one riot during the sample period. On average, the proportion of cells experiencing either a protest or a riot in any given month is around 5 percent.

3 Individual-Level Analysis: Daily perceived temperature anomalies and attitudes

We estimate the effect of perceived temperature (measured via the two components, T and F, of the heat index in equation 1) on self-reported attitudes and intentions as follows

$$\begin{aligned} attitude_{ictmd} &= \alpha + \beta_1 T_{itmd} + \beta_2 F_{itmd} + \beta_3 P_{itmd} + \overline{\boldsymbol{C}}_{\boldsymbol{cm}}{}'\boldsymbol{\delta} \\ &\quad + \boldsymbol{X}'_{itmd}\boldsymbol{\gamma} + \eta_c + \psi_{tmd} + \epsilon_{ictmd} \end{aligned} \tag{3}$$

where $attitude_{ictmd}$ denotes mistrust in government (measured via the six questions outlined above), voting intentions and intentions to protest for respondent living in location i in cell c interviewed in year t, month m and day d. See section 2.1 and appendix C for more details. The focus on trust is motivated by findings in the political science literature that relate trust to violence (Warren, 2017; Reemtsma, 2012). The main regressors of interest are air temperature (T_{itmd}) and the *feel factor* (F_{itmd}) on the exact day of interview (i.e. day d in month m and year t) at the precise location of the interview of respondent i. For completeness, we also control for precipitation (P_{itmd}). We estimate equation 3 by OLS.

We also include $\overline{\boldsymbol{C}}_{\boldsymbol{cm}}$, which consists of long term averages of T_{itmd}, F_{itmd} and P_{itmd} for month m in each cell c.[7] Because we include $\overline{\boldsymbol{C}}_{\boldsymbol{cm}}$, the variables T_{itmd} and F_{itmd} can be interpreted as daily deviations or anomalies on day d in month m from the long run average of month m and cell c. Whilst long term climatic averages are likely to be associated with numerous underlying factors, such as, for instance, institutional quality (Rodrik et al., 2004; Acemoglu et al., 2002), daily deviations from these long term means are plausibly exogenous. Finally, $\boldsymbol{X}'_{itmd}$ consists of characteristics[8] of respondent i; η_c and ψ_{tmd} are cell and date (i.e. for day d in month m and year t) fixed effects, respectively. We estimate Spatial HAC (Conley, 1999) standard errors.[9]

We also re-estimate equation 3 including lags for T_{itmd} and F_{itmd} for the two days before (T_{itmd-1}, T_{itmd-2} and F_{itmd-1}, F_{itmd-2}) and leads for the two days after (T_{itmd+1}, T_{itmd+2} and F_{itmd+1}, F_{itmd+2}) the date of the interview. Moreover, as a placebo check we estimate the effect of perceived temperature on self-reported experiences that occurred before year t, month m and day d and should thus bear no relation to T_{itmd}, F_{itmd} and P_{itmd}.

[7] We use the years 2009 to 2014 to construct $\overline{\boldsymbol{C}}_{\boldsymbol{cm}}$ for each month and each cell.

[8] As covariates we include dummy variables for the respondent living in a shack, or having no formal education, being employed, his or her religion being Christian, a female dummy, dummies for the respondent's race being black and one for mixed race. We also control for the respondent's age and for the latitude and longitude of the location of the respondent's residence.

[9] Spatial HAC Conley standard errors use *reg2hdfespatial* programme by (Fetzer, forthcoming) based on (Hsiang, 2010). We allow for 180km radius and one day lag.

3.1 Results: Daily perceived temperature anomalies, mistrust in government and voting intentions

The dependent variables are the six dummies for mistrust in government and the indicator variable taking the value 1 if the respondent intends to vote for a party to which the current head of state is not affiliated. See section 2.1 and Appendix C for more detail. We also collapse all six dummies into a single index using principal component analysis.[10] To make the magnitudes meaningful, we create a z-score of the first principal component.

Graphical analysis: The maps reported in figure 2 plot averages for air temperature (panel a), the feel factor (panel b) and the first principal component derived from the six questions for trust in government (panel c) for each 1×1 degree latitude and longitude cells. Average levels of trust show a strong correlation with the feel factor, F, where higher values of F correspond to higher levels of reported mistrust (panels b and c). By contrast, the correlation between air temperature, T, and trust in government appears considerably weaker (panels a and c). These descriptive patterns tally with findings in biometeorology highlighting the importance of humidity in determining perceived temperature (Alahmer et al., 2012; Vellei et al., 2017; Maley et al., 2018; Makowiec-Dabrowska et al., 2019).

Main results: In panel A of table 1 we regress our seven dependent variables (six dummies and their principal component) on air temperature, T, and the feel factor, F, *on the exact day and at the precise location* of the interview. Since we also control for local long term averages in air temperature and the feel factor via $\overline{\boldsymbol{C}}_{\boldsymbol{cm}}{}'$ in equation 3, T_{itmd} and F_{itmd} on the day and location of interview can be interpreted as deviations from long term averages, i.e. anomalies, which are likely to be exogenous. Across all six questions, perceived temperature increases self-reported mistrust. A 1°C increase in perceived temperature due to humidity, wind and solar radiation increases mistrust by between 0.5 and 1 percentage points. By contrast, air temperature has no consistent, significant effect on mistrust. The estimates in column 7 suggest a 1°C positive anomaly increases mistrust by 0.03 of a standard deviation. Similarly, a 1°C positive anomaly in the feel factor (F) increases the probability of intending to vote for a party other than the current head of state by 0.8 percentage points (see column 8).

Leads and lags: In panel B of table 1 we also control for air temperature and the feel factor on the location of interview two days before and two days after the interview (T_{itmd-1}, T_{itmd-2}, T_{itmd+1}, T_{itmd+2} and F_{itmd-1}, F_{itmd-2} and F_{itmd+1}). The parameter estimates for the two leads and two lags are small in size and yet precisely estimated. The magnitudes for the coefficient estimates on the actual day of interview, by contrast, remain virtually unchanged.

[10] We use the first principal component.

Placebos: Finally, in panel C of table 1, we carry out a number of placebo checks where we regress various past experiences of respondents on T and F. Since it is impossible for weather today to affect experiences in the past, we would expect coefficients close to zero, which is what we find.

3.2 Results: Perceived temperature, ethnicity and trust

Our findings suggest that the effect of perceived temperature on mistrust is stronger across ethnic lines. First, we estimate whether the effect of perceived temperature varies if the respondent's and the president's ethnicity are not the same. For this, we define a dummy taking the value one if the respondent and the president have the same ethnicity and interact it with the feel factor (F) on the day of the interview. The base category for this consists of respondents, whose ethnicity is different to the president. Column (2) of table 2 shows that the effect of perceived temperature on mistrust in government is significantly larger if the respondent has a different ethnicity to the president.

In column (3) we test whether the association between perceived temperature and distrust is stronger in ethnically diverse countries using the Ethnic Fragmentation index developed by Alesina et al. (2002), which uses the Herfindahl–Hirschman formula of the sum of squares of the proportions of each ethnic group within the country to capture the extent of ethnic diversity. For countries with a fragmentation index below the median, the association between perceived temperature and distrust is around 0.024 of a standard deviation weaker.

Finally, in column (4) we match the ethnic homeland respondents reside in to historical slave trade data, which has been shown to erode trust Nunn and Wantchekon (2011) (see appendix A for a map). We divide the sample into ethnicities with above and below median exposure to slave trade. In line with Nunn and Wantchekon (2011), we find that the effect of perceived temperature is 0.016 weaker for ethnicities that experienced relatively little slave trade.

3.3 Results: perceived temperature anomalies and intentions to protest

Crucially for the link between attitudes and conflict, the results also show that in poor countries, where individuals have reasons for dissatisfaction and grievances, perceived temperature increases self-reported intentions to protest. Using data on the incidence of poverty provided by the World Bank, we define a dummy for whether the percentage of individuals living on less than USD1.90 a day in the country each respondent resides in lies below the median (denoted as "rich country"). As columns (5) and (6) of table 2 show, the effect of perceived temperature on trust and on voting intentions is stronger in poor countries, albeit not statistically significant.

Crucially for our purposes, however, a 1°C positive perceived temperature anomaly increases self-reported intentions to protest by around 0.8 percentage points in poor countries. This finding tallies with a recent analysis of Manacorda and Tesei (2020), which shows that the effect of mobile technologies on protests is stronger in countries with slow economic growth.

3.4 Robustness

We start to investigate the robustness of our estimates by re-estimating equation 3 including all four components of the heat index separately, rather than via the algorithm in section 2.2. Since all four variables have very different scales and units and to make their magnitudes comparable, we convert each into a z-score. The parameter estimates in column (8) of table 2 show that amongst all components humidity has the strongest effect on mistrust. This finding tallies with the importance of humidity for perceived temperatures highlighted by meteorologists (Tsutsumi et al., 2007; Alahmer et al., 2012) and the major role humidity plays in regulating serotonin uptake (Tiihonen et al., 2017). The second largest estimate is for solar radiation.

We also subject our estimates to a battery of robustness checks and report the results in appendix D. Our results are robust to i) adding country fixed effects to our main specification, ii) using cell-by-month fixed effects, iii) using sub-national region-by-month fixed effects, iv) using sub-national region fixed effects rather than cell fixed effects and v) using the sum of the six dummy variables rather than the 1^{st} principal component.

4 Sub-National Cell-Level Analysis: Monthly perceived temperature anomalies and civil unrest

The second part of the paper examines the effect of perceived temperature (measured via the components T and F of the heat index in equation 1) on incidences of protests and riots. For this part of the analysis, we divide the African continent into 2,757 sub-national cells of size 1×1 degree latitude and longitude (approximately 110km at the equator) provided by Harari and La Ferrara (2018). Using ACLED project data, we construct a panel where each of these cells contributes one observation per month for the years 2009 to 2018. The dependent variable $unrest_{ctm}$ takes the value 100 if at least one protest or riot occurred in cell c in month m and year t. We estimate

$$unrest_{ctm} = \beta_1 T_{ctm} + \beta_2 F_{ctm} + \beta_3 P_{ctm} + \overline{\boldsymbol{C}}_{\boldsymbol{cm}}{}' \boldsymbol{\delta} + \eta_c + \rho_t + \phi_m + \mu_c \times \tau + \epsilon_{ctm} \quad (4)$$

where T_{ctm} and F_{ctm} denote air temperature and the feel factor in equation 1 in cell c in month m and year t, respectively. We also control for cell and month specific precipitation, P_{ctm}. As before, we include a vector, $\overline{\boldsymbol{C}}_{\boldsymbol{cm}}{}'$, containing the long run means of the variables T_{ctm}, F_{ctm} and P_{ctm} for each month m in cell c.[11] This allows us to interpret T_{ctm}, F_{ctm} and P_{ctm} as anomalies, i.e. deviation from long run local means. We also include fixed effects for each cell (η_c), year (ρ_t) and month (ϕ_m) and country-specific time trends ($\mu_c \times \tau$) and also include the lagged dependent variable, $riot_{ctm-1}$. We estimate equation 4 by OLS.

4.1 Results: Monthly perceived temperature anomalies and civil unrest

Graphical analysis: The three maps in figure 3 show average air temperature (panel a), the average feel factor (panel b) and the total number of protests and riots (panel c) for all 2,757 cells in Africa for the years 2009 to 2018. The maps indicate that areas with higher temperatures and areas where the feel factor is particularly high (i.e. perceived temperature due to humidity, wind and solar radiation) are more likely to experience more protests and riots.

Main results: The parameter estimates based on equation 4 whilst controlling for long term cell averages are reported in table 3. Both air temperature and feel factor anomalies increase incidences of riots or protests, which is robust across different specifications (columns 1 and 2). The effect, however, is larger for the feel factor (F), around 0.3 percentage points, than for air temperature (T), around 0.1 percentage points. Column (3) considers a different dependent variable: incidence of strategic violence defined as events that trigger the onset of violence. This type of conflict is likely to be driven by tactical, strategic and political factors rather than by attitudes (Passarelli and Tabellini, 2017). Accordingly, we find with parameter estimates close to zero yet precisely estimated.

Ethnic composition: As before, we estimate whether the effect of perceived temperature varies by the ethnic composition of cells. In column (4) of table 3, we interact the feel factor (F) with a dummy taking the value one if cell c contains only one historical ethnic homeland. As a consequence, the coefficient on the feel factor (F) in column 4 denotes the effect of perceived temperature for cells with more than one ethnic homeland, which are more

[11] We use the years 2008 to 2018 to construct these averages.

ethnically diverse. The parameter estimates show that the effect of perceived temperature is 0.08 percentage points larger for ethnically diverse cells.

Poverty: In column (5) of table 3 we test whether the effect of perceived temperature is stronger for cells located in poor countries. As before, we use the proportion of individuals living under USD1.90 a day provided by the World Bank to define a dummy taking the value 1 if the cell is located in a country where the incidence of poverty is below the median. Akin to the results on intentions to protest shown in table 2, the parameter estimates show that the effect of perceived temperature on the incidence of riots and protests is significantly stronger in poor countries.

4.2 Results: importance of agricultural incomes

Four pieces of evidence all suggest that the effect of perceived temperature on incidences of protests and riots does not operate through changes in agricultural income.

First, we re-estimate equation 4 adding leads and lags of T and F for the three months before and three months after m. As figure 4a shows, anomalies in the three months before and after have a negligible effect on protests and riots. The effect of perceived temperature anomalies in the same month, by contrast, remains large. Since it is likely to take a whole agricultural season—almost a year long—for weather fluctuations to affect incomes (Harari and La Ferrara, 2018), effects of perceived temperature within the same month are unlikely to be the result of income changes.

Second, we estimate the effect of perceived temperature anomalies along the crop-calendar. The effect of the weather on agricultural productivity and thus agricultural income is considerably stronger during growing seasons. We define the growing season for each of the 2,757 cells by combining the two independent data sources outlined in section 2.1. The map in appendix A shows the major crops and is very similar to the one reported by (Harari and La Ferrara, 2018). Using information on each growing season, we group the 12 months of the year into 6 groups always in relation to the harvesting month of the cell-specific major crop (6-11 months before, 3-5 months before, 0-2 months before the harvest and 1-3 months after, 4-6 months after and 6-11 months after the harvest) and estimate the effect of perceived temperature for these time intervals. The estimates in figure 4b show that the effect of perceived temperature is remarkably stable along the crop calendar.

Third, in column (7) of table 3 we include all four parts of the heat index separately. As with the estimates on trust, humidity shows the strongest effect on protests and riots. Whilst human perception of heat is very susceptible to humidity (see, Tsutsumi et al., 2007; Alahmer et al., 2012), Zhao et al. (2005) point out that short term fluctuations in humidity have a negligible effect on agricultural output.

Fourth, we analyse agricultural labour productivity directly by using yearly data provided by the World Bank on agriculture, forestry, and fishing, value added per worker between 2009 and 2018.[12] We calculate yearly values for our meteorological variables for each country, merge these to the World Bank country/year panel and regress agricultural value added on T and F. The results in column (8) of table 3 show that yearly temperature bears a negative relation to agricultural value added per worker of around 4 percent, which tallies with the results found by Dell et al. (2012). By contrast, the coefficient on perceived temperature due to humidity, wind and radiation,F, is close to zero, around 1 percent.

4.3 Results: Income and short-term effects are not mutually exclusive

Comparing the effect of perceived temperature highlighted in section 4.2 to the effect operating via agricultural income suggest that both effects are complementary and roughly equally important.

Following the methodology proposed by Harari and La Ferrara (2018), for each cell c in month m we calculate two averages: i) average air temperature during months falling *inside the growing season* prior to month m (T_g) and ii) average air temperature during months falling *outside of the growing* season prior to month m (T_{ng}). Since crop growth is particularly susceptible to climatic fluctuations during growing seasons an effect of temperature via agricultural income implies an effect of T_g but not of T_{ng}.

Column (6) of table 3 shows that a 1°C increase in air temperature during the previous growing season (T_g) increases incidences of conflict by around 0.4 percentage points. By contrast, the parameter estimate for the average air temperature outside of the previous growing season (T_{ng}) is very close to zero and yet precisely estimated. The coefficient on the feel factor, F, in the same month, however, remains large, around 0.5 percentage points.

Taken together these findings suggests that temperature affects protests and riots by changing agricultural incomes as well as via a more direct, short-term effect, possibly operating through trust.

[12] Value added denotes the net output of a sector after adding up all outputs and subtracting intermediate inputs. Data are in constant 2010 U.S. dollars. Agriculture corresponds to the International Standard Industrial Classification (ISIC) tabulation categories A and B (revision 3) or tabulation category A (revision 4), and includes forestry, hunting, and fishing as well as cultivation of crops and livestock production. Values are reported in constant 2010 US$. The data are freely available under `https://data.worldbank.org/`. Accessed July 2020.

5 Conclusion

The findings presented in this paper document that temperature as perceived by individuals raises self-reported mistrust in their government. Perceived temperature also increases self-reported intentions to vote against the current government and, in poor countries, to protest. These findings are borne out by estimates showing a positive effect of temperature on actual incidences of protests and riots. The finding that these effects are particularly strong in ethnically diverse and in poor countries gives rise to numerous policy implications. High levels of mistrust, for instance, could be mitigated by the general population feeling fairly represented in the policy making process, particularly marginalised ethnicities. Similarly, increasing government transparency and accountability might also attenuate any increases in mistrust. Finally, our results also indicate that the effect we highlight in this paper complements rather than excludes the widely documented effect of climatic changes operating via agricultural incomes. As such, our paper highlights a new channel through which the climate affects economic outcomes, which might be of interest to policy makers.

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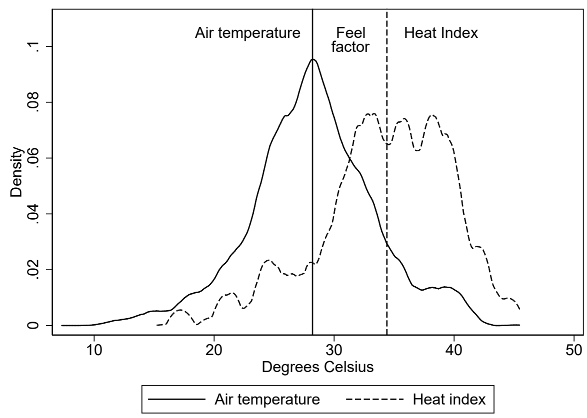
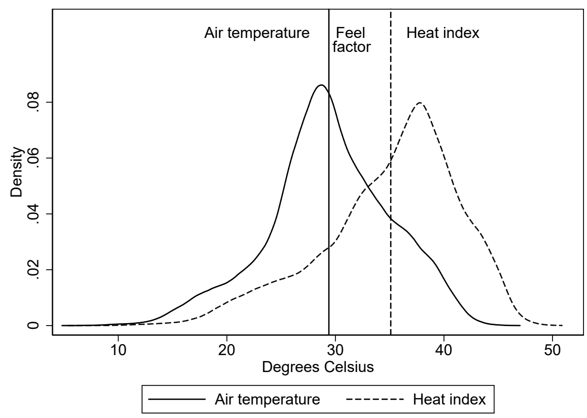
Figures

Figure 1: Air temperature, perceived temperature, attitudes and civil unrest

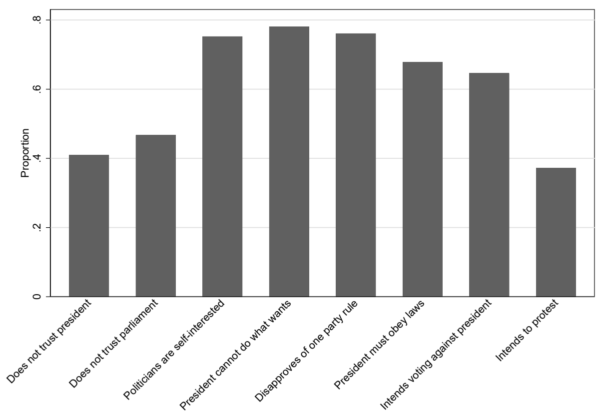
(a) Air temperature and heat index 2014-15



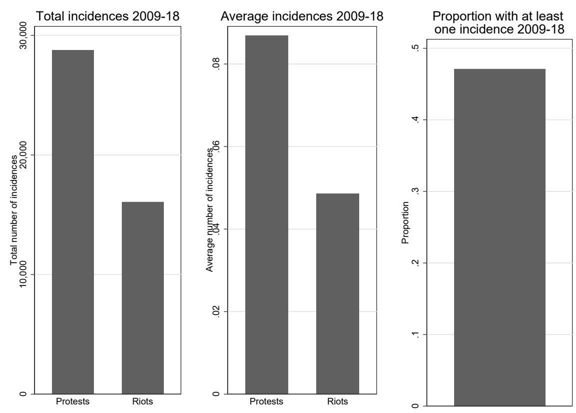
(b) Air temperature and heat index 2009-18



(c) Self-reported attitudes 2014-15

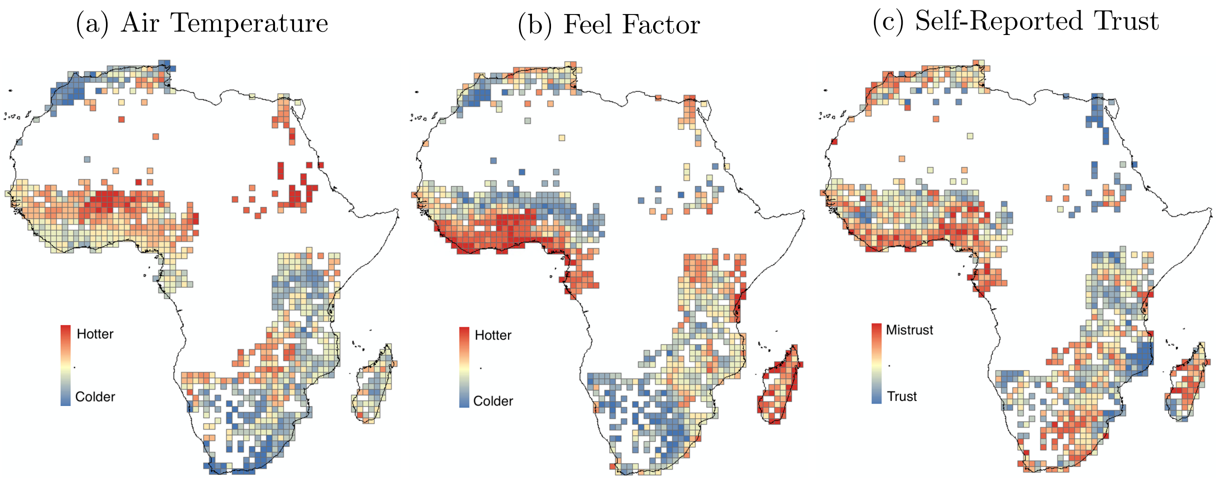


(d) Incidences of protests and riots 2009-18



Notes: the figures report summary statistics on perceived temperature, trust, intentions to vote and to protest, and civil unrest; panel a reports the air temperature and perceived temperature measured via the heat index in equation 1 in degree Celsius for the Afrobarometer sample for the years 2014 to 2015 panel b reports the air temperature and perceived temperature measured via the heat index in equation 1 in degree Celsius for the whole of Africa for the years 2009 to 2018; panel c reports the proportion of Afrobarometer respondents reporting mistrust in their government, voting intentions and intentions to protest; panel d provides summary statistics on protests and riots based on ACLED.

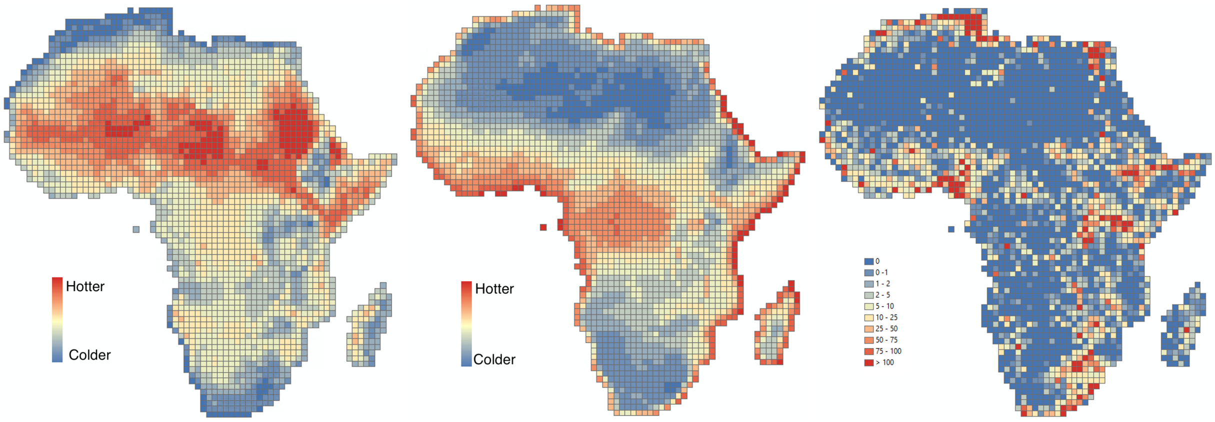
Figure 2: Air Temperature, Perceived Temperature and Trust in Africa



Notes: the maps report air temperature, perceived temperature and trust for Afrobarometer respondents; panel a reports the mean air temperature on the day of interview for Afrobarometer respondents 2014-15, blue denotes lower and red higher values; panel b reports the mean feel factor (i.e. the perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2) on the day of interview for Afrobarometer respondents 2014-15, blue denotes lower and red higher values; panel c reports the mean trust in government reported by Afrobarometer respondents 2014-15, values are based on the first principal component of the six questions used to measure trust in government, blue denotes higher trust and red lower trust in government.

Figure 3: Air temperature, perceived temperature and civil unrest in Africa

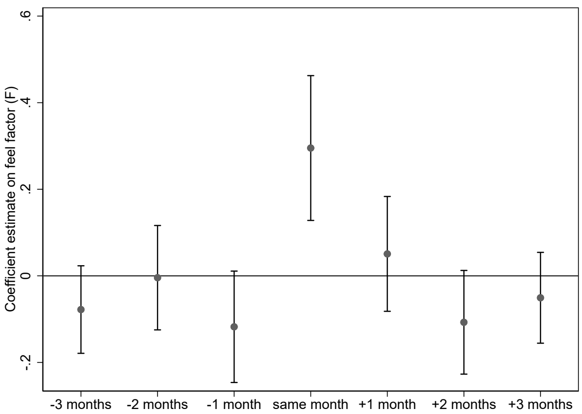
(a) Air Temperature (b) Feel Factor (c) Protests and Riots



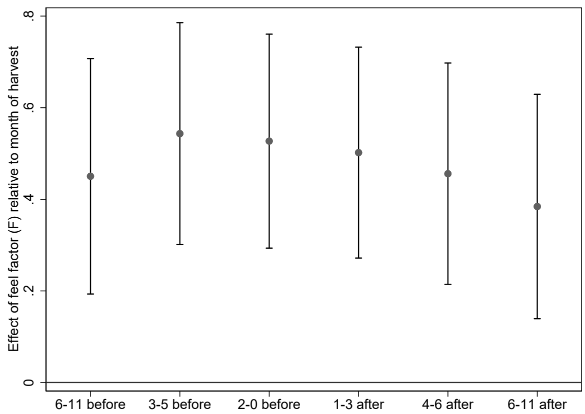
Notes: the maps report air temperature, perceived temperature and incidences of protests and riots for the years 2009 to 2018; panel a reports the mean air temperature per cell for the years 2009 to 2018, blue denotes lower and red higher values; panel b reports the mean feel factor (i.e. the perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2) per cell for the years 2009 to 2018, blue denotes lower and red higher values; panel c reports the total number of protests and riots occurring in each cell for the years 2009 to 2018, blue denotes lower and red higher values.

Figure 4: Effect of perceived temperature on civil unrest by month and along crop calendar

(a) Effect on civil unrest by month



(b) Effect on civil unrest along crop calendar



Notes: the figures show how the effect of perceived temperature on protests and riots varies by month and along crop calendar; dots report parameter point estimates from OLS regression for *Feel factor (F)* (i.e. perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2); vertical lines denote 95% confidence intervals; dependent variable takes value 100 if cell c experienced at least one protest or riot in month m; panel a adds 3 months leads and lags for regressor *Feel factor (F)*; panel b interacts *Feel factor (F)* with six dummies indicating the position of month m relative to the cell-specific crop growing calendar; *6-11 before* =1 if month m falls 6 to 11 months before the harvest month of cell c's major crop; *3-5 before* =1 if month m falls 3 to 5 months before the harvest month of cell c's major crop; *0-2 before* =1 if month m falls 2 to 1 months before or on the same month as the harvest of cell c's major crop; *1-3 after* =1 if month m falls 1 to 3 months after the harvest month of cell c's major crop; *4-6 after* =1 if month m falls 4 to 6 months after the harvest month of cell c's major crop; *6-11 after* =1 if month m falls 6 to 11 months after the harvest month of cell c's major crop; spatial HAC Conley standard errors with 180km radius and one month lag.

Tables

Table 1: Perceived temperature, trust in government and voting intentions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables:	=100 if resp. trusts in president	=100 if resp. trusts in parliament	=100 if resp. believes that politicians are out for themselves	=100 if resp. disapproves of one party rule	=100 if resp. disapproves of president can do what he wants	=100 if resp. believes that president must obey the laws	1^{st} principal component z-score for trust	=100 if resp. intends to vote against president
	Panel A: Effect of perceived temperature on day of interview							
Feel factor (F)	0.822 * *	1.138***	0.800***	0.764***	0.644 * *	0.472	0.031***	0.779 * *
on day of interview	(0.324)	(0.333)	(0.284)	(0.247)	(0.271)	(0.315)	(0.007)	(0.332)
Air temperature (T)	0.229	0.376 * *	−0.121	−0.019	−0.243*	−0.228*	0.002	0.455***
on day of interview	(0.172)	(0.157)	(0.123)	(0.106)	(0.136)	(0.133)	(0.004)	(0.143)
	Panel B: Leads and lags for the two days before and after interview							
Feel factor (F)	0.705 * *	1.185***	0.857***	0.610 * *	0.546*	0.460	0.029***	0.679*
on day of interview	(0.357)	(0.367)	(0.316)	(0.280)	(0.313)	(0.336)	(0.008)	(0.365)
Feel factor (F) on:								
1 day before interview	−0.283	−0.282	−0.432	0.068	−0.183	−0.071	−0.008	−0.100
	(0.349)	(0.349)	(0.290)	(0.275)	(0.318)	(0.325)	(0.007)	(0.355)
2 days before interview	0.466	0.287	−0.028	0.171	0.303	0.058	0.009	0.174
	(0.339)	(0.345)	(0.322)	(0.267)	(0.304)	(0.321)	(0.007)	(0.361)
1 day after interview	0.182	−0.087	0.201	0.271	0.157	−0.210	0.004	0.145
	(0.342)	(0.336)	(0.332)	(0.272)	(0.293)	(0.346)	(0.007)	(0.353)
2 days after interview	−0.058	−0.210	0.023	0.067	0.159	0.289	0.000	0.122
	(0.361)	(0.352)	(0.303)	(0.271)	(0.306)	(0.334)	(0.007)	(0.385)
	Panel C: Placebos: Dependent variable = 100 if respondent has ever							
	Contacted a Party official	Contacted a Trad. leader	Contacted a Rel. leader	Contacted a MP	Contacted a Govt agency	Feared crime	Felt unsafe	Physically attacked
Feel factor (F)	−0.019	0.125	−0.020	−0.088	−0.097	−0.187	−0.011	−0.142
on day of interview	(0.220)	(0.297)	(0.307)	(0.286)	(0.193)	(0.218)	(0.279)	(0.189)
Observations	50,018	50,022	50,012	50,002	50,021	50,017	49,968	48,828
Cell & Date fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Cell Climate average	yes	yes	yes	yes	yes	yes	yes	yes

Notes: table shows parameter estimates for regression of self-reported trust and voting intentions on perceived temperature; *Feel factor (F)* denotes perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2 at location and on day of interview; *Air temperature (T)* denotes air temperature at location and on day of interview; Panels A and B: dependent variables = 100 if respondent does not trust in the president (column 1), does not trust in parliament (column 2), believes politicians are out for themselves (column 3), disapproves of one party rule (column 4), disapproves of president doing what he/she wants (column 5), believes president should obey the laws (column 6), would vote for party that current president is not affiliated to (column 8), dependent variable in column 7 the first principal component (z-score) of dependent variables in columns 1 to 6; Panel C: dependent variables take value 100 if respondent ever contacted a party official (column1), a traditional leader (column 2), a religious leader (column 3), a member of parliament (column 4) or a government agency (column 5) or if respondent fears crime in own home (column 6) or feels unsafe (column 7) or physically attacked (column 8); estimates are based on OLS; spatial HAC Conley standard errors with 180km radius and one day lag are reported in parentheses.

Table 2: Perceived temperature, trust in government and intentions to vote and protest

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables:	1st principal component for trust	1st principal component for trust	1st principal component for trust	1st principal component for trust	1st principal component for trust	=100 if resp. intends to vote against president	=100 if resp. intends to protest	1st principal component for trust
Base category:		Different ethnicity to president	Ethnically heterogenous country	High slave trade	Poor country	Poor country	Poor country	
Feel factor (F)	0.031∗∗∗	0.031∗∗∗	0.044∗∗∗	0.040∗∗∗	0.041∗∗∗	1.244∗∗∗	0.798 ∗ ∗	
on day of interview	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)	(0.470)	(0.407)	
Feel factor (F)		−0.028∗∗∗						
× same ethnicity		(0.008)						
Feel factor (F)			−0.024 ∗ ∗					
× ethnically homogenous			(0.012)					
Feel factor (F)				−0.016∗				
× low slave trade				(0.008)				
Feel factor (F)					−0.019	−0.688	−1.684∗∗∗	
× rich country					(0.013)	(0.650)	(0.541)	
Air temperature (zscore)								0.004
								(0.021)
Humidity (zscore)								0.112∗∗∗
								(0.026)
Wind speed (zscore)								0.014
								(0.010)
Solar radiation (zscore)								0.020∗
								(0.011)
Rainfall (zscore)								−0.010
								(0.007)
Observations	49,968	49,968	45,185	49,968	49,484	49,968	48,828	45,349
Cell & Date fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Cell Climate average	yes	yes	yes	yes	yes	yes	yes	yes

Notes: table shows parameter estimates for regression of self-reported trust, voting intentions and intentions to protest on perceived temperature by individual and country characteristics; dependent variable is z-score of first principal component for the six measurements for mistrust (in columns 1 to 5 and 8); dependent variable = 100 if respondent would vote for a party that current president is not affiliated to (in column 6); dependent variable = 100 if respondent would participate in protest march or demonstration if they had a chance (in column 7); *Feel factor (F)* denotes perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2 at location and on day of interview; *same ethnicity* =1 if respondent is of same ethnicity as president; *ethnically homogenous* = 1 if heterogeneity index of country respondent resides in is below the median; *low slave trade* =1 if historical slave trade of respondent's ethnicity is below median; *rich country* = 1 if proportion of population living under USD1.90 is below the median; *Air temperature* is the z-score of the air temperature, *Humidity* is the z-score of humidity, *Wind speed* is the z-score of wind speed, *Solar radiation* is the z-score of solar radiation, *Rainfall* is the z-score of precipitation, all at location and on day of interview; estimates are based on OLS; spatial HAC Conley standard errors with 180km radius and one day lag are reported in parentheses.

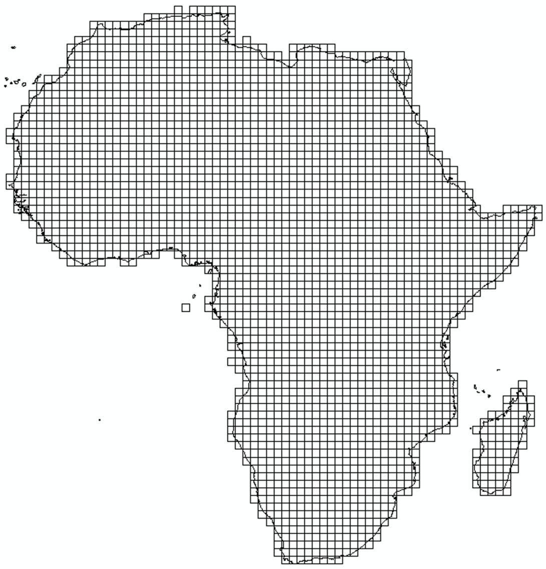
Table 3: Perceived temperature and incidences of protests and riots

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	= 100 if cell c in month m experiences at least one							Log agricultural GVA per worker
	Riot or protest	Riot or protest	Strategic violence	Riot or protest	Riot or protest	Riot or protest	Riot or protest	
Feel factor (F)	0.316***	0.322***	−0.026	0.361***	0.368***	0.499***		0.014
	(0.092)	(0.085)	(0.052)	(0.088)	(0.088)	(0.116)		(0.033)
Air temperature (T)	0.135***	0.087***	−0.024	0.085***	0.111***	0.139***		−0.039*
	(0.033)	(0.030)	(0.018)	(0.032)	(0.031)	(0.048)		(0.020)
Feel factor (F) × single ethnicity				−0.083*				
				(0.046)				
Feel factor (F) × rich country					−0.101**			
					(0.049)			
Average temperature inside previous growing season						0.373***		
						(0.098)		
Average temperature out of previous growing season						0.081		
						(0.107)		
Air temperature (zscore)							0.399**	
							(0.170)	
Humidity (zscore)							1.118***	
							(0.262)	
Wind speed (zscore)							0.084	
							(0.119)	
Solar radiation (zscore)							0.387**	
							(0.195)	
Rainfall (zscore)							−0.012	
							(0.120)	
Observations	330,840	330,840	330,840	330,840	330,840	242,403	330,840	404
Cell, Year & Month fixed effects	yes	yes	yes	yes	yes	yes	yes	
Long term cell average climate	yes	yes	yes	yes	yes	yes	yes	
Country specific time trend	no	yes	yes	yes	yes	yes	yes	
Lagged dependent variable	no	yes	yes	yes	yes	yes	yes	yes
Country fixed effects								yes
Data source	ACLED	ACLED	ACLED	ACLED	ACLED	ACLED	ACLED	World Bank

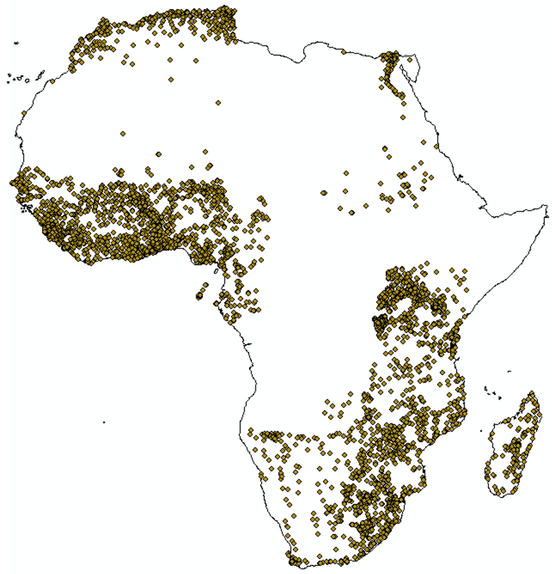
Notes: table shows parameter estimates for regression of incidences of protests and riots on perceived temperature; dependent variable =100 if cell c experienced at least one protest or riot in month m (in columns 1,2, 4, 5, 6 and 7); dependent variable =100 if cell c experienced at least one incidence of strategic violence in month m (in column 3); dependent variable is log Gross Value Added (GVA) per worker for the agricultural sector (in column 8); *Feel factor (F)* denotes perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2 for cell c in month m; *Air temperature (T)* denotes air temperature for cell c in month m; *single ethnicity* = 1 if cell c contains only one ethnic homeland; *rich country* = 1 if proportion of population living under USD1.90 is below the median; *Average temperature inside previous growing season* is the average of air temperature for months in previous year to month m, which fall inside the cell-specific growing season; *Average temperature out of previous growing season* is the average of air temperature for months in previous year to month m, which fall outside of the cell-specific growing season; estimates are based on OLS; spatial HAC Conley standard errors with 180km radius and one month lag are reported in parentheses.

A Additional Maps

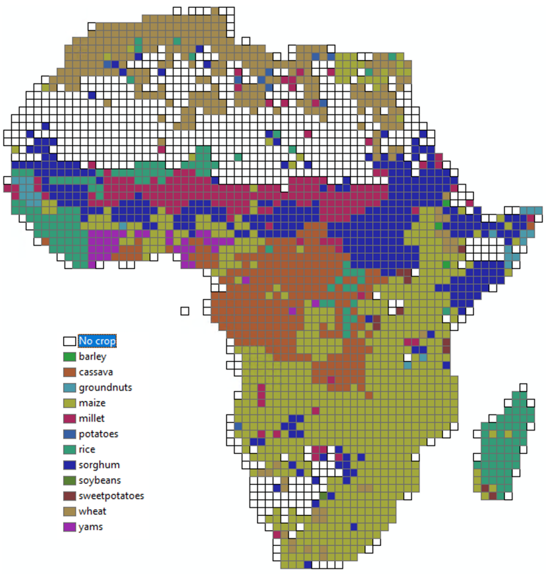
(a) 1×1 degree raster



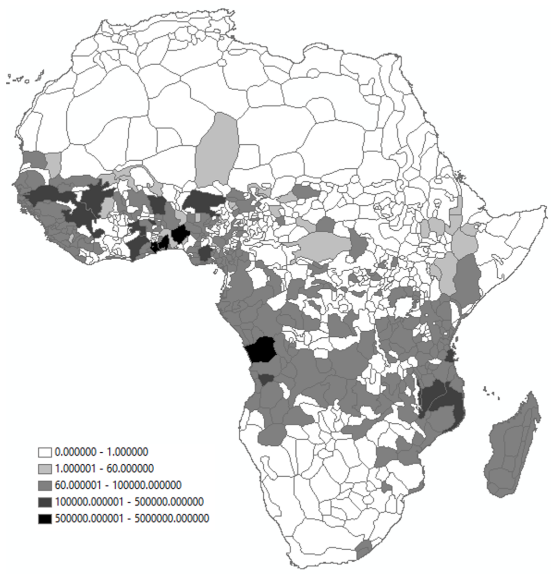
(b) Afrobarometer respondents



(c) Major cell-specific crops



(d) Historical slave trade



Notes: map a: shows the raster of the 2,757 1×1 degree latitude and longitude (approximately 110km at the equator) provided by Harari and La Ferrara (2018); map b: shows geographical coordinates of Afrobarometer respondents; map c: shows the major crop grown in each of the 2,757 cells; map d: shows ethnic homelands by total number of slave exports provided by Nunn and Wantchekon (2011).

B More detail about meteorological data and variables

For the analysis, daily climate data was taken from the ECMWF2 -ERA5 reanalysis for precipitation, surface air temperature, surface air dew temperature, wind speed and radiation for the study period. The variables are defined as follows:

- Surface air temperature and surface dewpoint temperature: Surface air temperature is the temperature of air near the earth surface. Surface air dewpoint temperature is the temperature near the surface to which a given air parcel must be cooled at constant pressure and constant water vapour content in order for saturation to occur; it measures the amount of humidity in the air. Both measures of temperature are calculated by interpolation between the lowest model level and the earth's surface after accounting for atmospheric conditions. Both are measured in kelvin at two metres from the surface of the earth at the weather station within the cell. Dew point and air temperature can be used to calculate water vapor pressure (Pha) using the following formulae $rh = 100 * (exp((17.625 * dewpoint)/(243.04 + dewpoint))/exp((17.625 * temperature)/(243.04 + temperature)))$, where rh is relative humidity and $Pha = (rh/100) * 6.105 * exp((17.27 * temperature)/(237.7 + temperature))$.

- Wind speed: The ERA5 contains two different measures of wind. 10m u-component of wind measures the eastward component of the 10m wind. It is defined as "... the horizontal speed of air moving towards the east, at a height of ten metres above the surface of the Earth, in metres per second". This variable can be combined with the V component of 10m wind to give the speed and direction of the horizontal 10m wind. 10m v-component of wind on the hand measures the northward component of the 10m wind. It is defined as "... the horizontal speed of air moving towards the north, at a height of ten metres above the surface of the Earth, in metres per second". We combine the u-component (u) and v-component (v) of wind to calculate overall windspeed as follows: $\sqrt{u^2 + v^2}$

- Surface net solar radiation: The ERA5 defines Surface net solar radiation as the "Amount of solar radiation (also known as shortwave radiation) reaching the surface of the Earth (both direct and diffuse) minus the amount reflected by the Earth's surface. Radiation from the Sun (solar, or shortwave, radiation) is partly reflected back to space by clouds and particles in the atmosphere (aerosols) and some of it is absorbed. The rest is incident on the Earth's surface, where some of it is reflected. The difference between downward and reflected solar radiation is the surface net solar radiation". It is measured in joules per square metre (J/m^2). In order to calculate the solar radiation absorbed by the human body, one has to make several assumptions about the size, shape and position of the human body. In table 4 we show that our results are remarkably stable across different assumptions regarding the shape, size and position of the human body. We follow the methodology suggested by Kenny et al. (2008) and make the following assumptions: i) We multiply solar radiation by 0.7 to account for the human body being in a sitting position, which we assume is how the interview takes place. The two alternatives considered by the authors are 0.78 for standing and 0.6 for crouched. ii) We multiply solar radiation by 0.483 to account for the albedo of the human body, for a medium sized man. The authors also give alternative values of 0.446 for a large man and 0.645 for a woman. iii) We multiply solar radiation by 0.21 to account for clothing. The authors provide 0.57 and 0.37 as alternative values. We chose 0.21 to account for the fact that individuals in hot countries wear appropriate clothing. In table 4, we try various combinations of these factors and the results remain remarkably stable across all specifications.

Table 4: Perceived temperature and trust - different measurements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:				1^{st} principal component				
Feel factor (F) on day of interview	0.026***	0.024***	0.026***	0.024***	0.018***	0.017***	0.028***	0.025***
	(.006)	(0.007)	(0.006)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)
Feel factor (F) on:								
Day before interview		−0.003		−0.003		−0.002		−0.003
		(0.006)		(0.006)		(0.005)		(0.007)
Two days before interview		−0.003		−0.003		−0.001		−0.004
		(0.007)		(0.007)		(0.00)		(0.007)
Day after interview		0.005		0.006		0.003		0.007
		(0.006)		(0.007)		(0.005)		(0.007)
Two days after interview		0.005		0.005		0.003		0.006
		(0.007)		(0.007)		(0.005)		(0.007)
Observations				50,034				
Date & cell fixed effects				yes				
XXX	0.6		0.78		0.7		0.6	
XXX	0.483		0.645		0.483		0.446	
XXX	0.37		21		0.57		0.21	

Notes: table shows parameter estimates for regression of self-reported trust on perceived temperature; dependent variable is z-score of first principal component of the six measurements for trust; *Feel factor (F) on day of interview* denotes perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2 at location and on day of interview; estimates are based on OLS; spatial HAC Conley standard errors with 180km radius and one day lag are reported in parentheses.

- Data on growing seasons: was taken from the Nelson database which collects information on the planting and harvesting dates of 19 major crops across several countries from six sources (FAO, USDA, USDA-FAS, USDA-NASS, IMD-AGRIMET, USDA-FAS) (see Sacks et al. (2010) for full description).

- Major crops for each cell: We identify the major crop for each cell with data from IFPRI. The IFPRI data was generated using the Spatial Production Allocation Model (SPAM). The model disaggregates crop specific production data by triangulating information from national and sub-national crop statistics, satellite data on land cover, maps of irrigated areas, biophysical crop suitability assessments, population density, secondary data on irrigation and rain fed production systems, cropping intensity, and crop prices (see Anderson et al. (2014) for full description).

C More detail on attitudinal questions

This paper uses round 6 of the Afrobarometer to measure mistrust in government, voting intentions and intentions to protest. The following is a list of variables used:

Variables used for mistrust in government

- **Does not trust president** uses the question *How much do you trust each of the following, or haven't you heard enough about them to say: The President?* Dependent variable takes value 1 if respondent answers either *Not at all* or *Just a little.*

- **Does not trust Parliament** uses the question *How much do you trust each of the following, or haven't you heard enough about them to say: The Parliament?* Dependent variable takes value 1 if respondent answers either *Not at all* or *Just a little.*

- **Politicians are out for themselves** uses the question *Do you think that the leaders of political parties in this country are more concerned with serving the interests of the people, or more concerned with advancing their own political ambitions, or haven't you heard enough to say?* Dependent variable takes the value 1 if respondent answers *More to serve their own political ambitions – strongly agree* or *More to serve their own political ambitions - agree* or *Neither agree nor disagree*

- **Disapproves of one party rule** uses the question *here are many ways to govern a country. Would you disapprove or approve of the following alternatives: Only one political party is allowed to stand for election and hold office?* Dependent variable takes the value 1 if respondent answers *Strongly disapprove* and *Disapprove.*

- **Disapproves of president can do what want** uses the question *There are many ways to govern a country. Would you disapprove or approve of the following alternatives: Elections and Parliament are abolished so that the president can decide everything?* Dependent variable takes the value 1 if respondent answers *Strongly disapprove* and *Disapprove.*

- **President must obey laws** uses the question *Which of the following statements is closest to your view? Choose Statement 1 or Statement 2. Statement 1: Since the President was elected to lead the country, he should not be bound by laws or court decisions that he thinks are wrong. Statement 2: The President must always obey the laws and the courts, even if he thinks they are wrong.* Dependent variable takes the value 1 if respondent answers *Agree with Statement 2* or *Agree very strongly with Statement 2*

Variable used for voting intention

- **Would vote against president** uses the question *If a presidential election were held tomorrow, which party's candidate would you vote for?* Dependent variables takes the value 1 if respondent's choice does not match the party of the current president.

Variable used for intention to protest

- **Intends to protest** uses the question *Here is a list of actions that people sometimes take as citizens when they are dissatisfied with government performance. For each of these, please tell me whether you, personally, have done any of these things during the past year. If not, would you do this if you had the chance: Participated in a demonstration or protest march.* We drop any individuals that have ever participated in a protest (9 percent). Dependent variable takes the value 1 if respondent answers *No, but would if had the chance.*

D Effect of perceived temperature on trust - robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variables:	1^{st} principal component for mistrust in government								Sum of dummies	
Feel factor (F) on day of interview	0.029***	0.027***	0.031***	0.026***	0.029***	0.026***	0.029***	0.026***	4.609***	4.341***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.006)	(0.007)	(0.006)	(0.007)	(1.050)	(1.146)
Feel factor (F) on:										
Day before interview		−0.008		−0.005		−0.003		−0.002		−1.140
		(0.007)		(0.007)		(0.007)		(0.007)		(1.077)
Two days before interview		0.008		0.011		−0.004		−0.005		1.229
		(0.007)		(0.007)		(0.007)		(0.007)		(1.081)
Day after interview		0.005		0.003		0.006		0.004		0.502
		(0.007)		(0.007)		(0.007)		(0.007)		(1.086)
Two days after interview		0.002		0.004		0.006		0.007		0.251
		(0.007)		(0.007)		(0.007)		(0.007)		(1.100)
Observations	49,968									
Cell fixed effects	yes	yes							yes	yes
Date fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country fixed effects	yes	yes								
Cell by Month fixed effects			yes	yes						
Region by Month fixed effects					yes	yes				
Region fixed effects							yes	yes		

Notes: table shows parameter estimates for regression of self-reported trust in government on perceived temperature; dependent variable is z-score of first principal component of the six measurements for trust (in columns 1 to 8); dependent variable is the sum of dummies for the six measurements for trust (in columns 9 and 10); *Feel factor (F) on day of interview* denotes perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2 at location and on day of interview; estimates are based on OLS; spatial HAC Conley standard errors with 180km radius and one day lag are reported in parentheses.

E More detail on violence

Riots and protest data was taken from ACLED Project. ACLED data contains information on the actors in a conflict, the dates and the location of the conflict. It also disaggregates and maps conflicts to highlight the fatalities and type of conflicts. For this study, we analyse the relationship between temperature and riots. ACLED defined riots as "violent demonstration, often involving a spontaneous action by unorganised unaffiliated members of society". This includes violent demonstrations, and mob violence. Protests on the other hand are "non-violent demonstrations, involving typically unorganised action by members of the society".