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PERCEIVED TEMPERATURE, TRUST AND CIVIL UNREST IN AFRICA

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Perceived Temperature, Trust and Civil Unrest in Africa

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Abstract

This paper documents a positive effect of short-term anomalies in temperature as perceived by the human body on mistrust and on civil unrest. To measure perceived temperature we construct a heat index that combines air temperature, humidity, wind speed and solar radiation. Using pan-African attitudinal data, we find that positive anomalies in perceived temperature on the exact day and at the precise location of the interview are associated with higher reported levels of mistrust. Effects are particularly strong for poorer individuals and individuals living in ethnically fragmented countries and in countries with low governmental efficiency. Moreover, monthly positive anomalies in perceived temperature are found to increase incidences of riots and protests. Evidence also suggests that this effect is independent of changes in income.

JEL Classifications: D74, Q54, N57

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1 Introduction

The links between climate and conflict are well documented. In a variety of different settings, hotter or drier climate has been associated with higher incidences of conflict (see Burke et al., 2015; for an overview). Much of the economics literature has focused on income as a pathway of impact where weather fluctuations lead to changes in income, which, in turn, affect the propensity of conflict (see Dell et al., 2014; for a general discussion). An increasing number of studies, however, have documented that higher temperatures can also lead to violence via a direct physiological, psychological effect on individuals by, for instance, altering serotonin levels in the body (Tiihonen et al., 2017). Nonetheless, there is still little evidence on the role of attitudes explaining the link between temperature and conflict or violence.

This paper documents a positive effect of temperature as perceived by the human body on self-reported mistrust in government and on incidences of protests and riots in Africa. Hot temperatures have been shown to affect attitudes (see Anderson et al., 2000; for an overview of the psychological literature) and we focus on trust, for which there are strong links with violence (see Kramer, 1999 for an overview and Acemoglu and Wolitzky, 2014; Rohner et al., 2013; for examples). We measure perceived temperature via an algorithm that combines various meteorological variables affecting the body's heat perception into an index. Our results show that respondents are significantly more likely to report mistrust in their government if the perceived temperature index *at the precise location and on exact the day of interview* is higher than its local long-term average. We also find a positive effect of perceived temperature anomalies on protests and riots in the same month, which appears to operate independently of agricultural income.

The algorithm we use to measure temperature as perceived by the human body is widely employed by meteorological services and translates air temperature, humidity, wind speed and solar radiation into a heat index. We draw data for each of these four meteorological variables from the ECMWF2-ERA5 reanalysis and combine it with the sixth round of the Afrobarometer, a representative attitudinal survey, which interviews nearly 54,000 respondents in 36 African countries. Using the exact geographical coordinates of respondents and the date of their interview, we calculate the heat index on the day of interview at the precise location where the interview takes place. Across six different questions approximating trust in government, the estimates show that a 1°C deviation from the long-term mean is associated with an almost 1 percentage point increase in self-reported distrust. Effects are particularly strong for individuals who are poor, unemployed, live in ethnically fragmented countries and in countries with low governmental efficiency. Using perceived temperature during the two days before or after the interview, by contrast, gives precisely estimated effects of zero. As a placebo, we estimate the effect on past experiences of respondents and also find precisely estimated parameters of zero. When we include the four variables of the heat index separately, we find that humidity has the strongest effect on mistrust.

For our second set of findings, we combine weather 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 (around 110km) and create a monthly panel for the years 2009 to 2018. We find that a 1°C positive anomaly in perceived temperature 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 or by ideological, religious considerations.

Four pieces of evidence all suggest that the effect of perceived temperature on civil unrest is independent of fluctuations in agricultural incomes. First, we find no effect for perceived temperature during the three months before or after. Since climatic fluctuations typically take more than a month to change agricultural output (Parvin et al., 2005), this finding points towards a direct effect of perceived temperature on conflict. Second, we investigate whether the effect is stronger during growing seasons, when crops are particularly sensitive to climatic fluctuations. For this, we identify the major crop cultivated in each of the 2,757 cells and find that the effect does not vary along the growing seasons. Third, when we substitute the heat index by its four components in our regressions, we find that humidity is the strongest predictor of conflict. 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, we regress annual data on country-specific agricultural gross value added (GVA) per worker on perceived temperature. Whilst we find that air temperature decreases agricultural GVA per worker slightly, the effect of perceived temperature due to humidity, wind and radiation is very close to and statistically indistinguishable from zero.

We also find evidence showing that high temperatures not only affect civil conflict via the direct channel highlighted in this paper but also by changes in agricultural incomes. For each cell and month, we calculate the average temperature in the preceding growing season, which is a key determinant of harvests and thus of agricultural incomes (Harari and La Ferrara, 2018). When we include this meteorological variable as an additional regressor, we find a large and positive effect on the incidence of riots and protests comparable in size to the one of perceived temperature in the same month. Taken together, these results suggest that the effect of temperature is twofold: higher temperatures affect conflict by decreasing agricultural incomes and also have a more direct, short-term effect on civil unrest.

By documenting an effect of perceived temperature on attitudes, 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; Larrick et al., 2011; Ranson, 2014). The psychological literature has focused on aggression arguing that increases in temperature change serotonin uptake, which has been linked to aggressive behaviour (Tiihonen et al., 1997, 2017). Experimental evidence has confirmed a strong relationship between temperature and behaviour commonly associated with violence (Vrij et al., 1994; Anderson et al., 2000; Almas et al., 2019). Other studies have also considered interactions between conflict and pathogens (Cervallati et al., 2017) and sporting events (Card and Dahl, 2011; Larrick et al., 2011).

By linking climatic events to attitudes, this paper also speaks to the economic literature on attitudes and 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), 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 under-explored. Also, attitudes in general 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 various data-sources, measurements and summary statistics. Section 3 explores the relationships between perceived temperature and trust. section 4 investigates the association between perceived temperature and conflict. Section 5 concludes.

2 Data and Conceptual Framework

2.1 Data and Measurements

Data on meteorological variables: Data on daily and monthly meteorological variables are taken from the ECMWF2-ERA5 reanalysis, which contains high resolution hourly 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 10m above the surface (in m/s) and surface dewpoint temperature (in°C), which we use to calculate humidity. See appendix B for more details.

Data on attitudes: Information on self-reported trust in government 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. The questionnaires contain questions on attitudes towards public institutions and elected officials and also include information on individual characteristics such as education, occupation and quality of living conditions. Upon request, the Afrobarometer also provides the geographical coordinates of respondents.

We use six questions to approximate trust in government. These inquire whether the respondent i) trusts the president, ii) trusts the parliament, 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.

Data on civil unrest: We measure civil unrest as incidences of i) protests and ii) riots drawn from the Armed Conflict Location and Event Data Project (ACLED), which collects information on all reported political violence and protest events for Africa and other continents.[2] For each event, ACLED reports the date, actors involved, fatalities and modalities along with the exact geographical coordinates. The ACLED categorises violent events into battles, violence against civilians, riots, protests and strategic developments. Our main 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.

Geographical coordinates and agricultural areas: We map climatic variables, attitudes and trust using the geographical grid provided by Harari and La Ferrara (2018), which divides the African continent into 2,757 1×1 degree latitude and longitude quadrangular cells (approximately 110km)—see map in appendix A. For each cell, we also calculate long

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

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

run averages for each month, which we use to model daily and monthly anomalies.

To identify the growing seasons for each cell's major crop, we combine two data sources. We identify the major crop cultivated in each cell using International Food Policy Research Institute (IFPRI) data (Anderson et al., 2014).[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

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 sun exposure decrease cooling whereas airflow increases it.

One of the most widely used measures for perceived temperature (Steadman, 1984, 1994) combines four meteorological variables—temperature, humidity, wind and solar radiation—into an index denoting what temperature would feel under fixed climatic conditions (i.e. if dew-point temperature were 14.0°C). This index is the basis for a variety of heat indices provided by, among others, the National Oceanic and Atmospheric Administration (NOAA), the U.S. National 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 as

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

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 body does not only depend on air temperature, T, but also on humidity, wind and solar radiation. The heat

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

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

[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.

index deviates from the temperature of the air 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 (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 of F, has been identified as particularly important in determining how temperature is perceived 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 Summary statistics

Figures 1a and 1b show the distributions of air temperature and the heat index from equation 1. For both the Afrobarometer sample (from 2014 to 2015 in panel a) and the ACLED sample (from 2009 to 2018 in panel b) the heat index exceeds air temperature by about 5 °C. This difference is the result of the feel factor, F, in equation 2. 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 close to the equator.

Figure 1c reports the average levels of trust as reported in the Afrobarometer. Overall, trust in government is relatively low. Just under half of respondents report not to trust the president or the parliament of their own country. Moreover, around three quarters believe that the motivations of politicians are selfish, 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.

Information on incidences of protests and riots are reported in figure 1d. For the years 2009 to 2018 the ACLED database reports a total of 28,762 protests and 16,080 riots for the whole of Africa. 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.

3 Daily anomalies in perceived temperature and trust

Our empirical strategy relates perceived temperature, measured via the two components (T and F) of the heat index in equation 1, and trust in government as follows

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

where $trust_{ictmd}$ is one of the six measures of trust in government described in section 2.1 for respondent living in location i in cell c interviewed in year t, month m and day d. 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 precise day of interview (i.e. day d in month m and year t) at the exact 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. 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, by contrast, are plausibly exogenous. Finally, $\boldsymbol{X}'_{itmd}$ consists of characteristics[8] of respondent i and we estimate Spatial HAC (Conley, 1999) standard errors.[9]

To improve identification, we re-estimate equation 3 in two ways. First, we include lags and leads for T_{itmd} and F_{itmd} for the two days before and the two days after the date of the interview. Second, 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 anomalies in perceived temperature and trust

The dependent variables for our analysis are the six dummies based on the six questions laid out in section 2.1 and Appendix C. 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.

The maps reported in figure 2 plot average air temperature (panel a) and the feel factor (panel b) in each 1×1 cell against the first principal component derived from the six questions for trust in government (panel c). Whilst average levels of trust do not map particularly well with air temperature, T, they show a strong correlation with the feel factor, F, where higher values of F correspond to higher levels of reported distrust. These descriptive patterns tally with research findings in biometeorology highlighting the importance of factors such as humidity in determining perceived temperature (Alahmer et al., 2012; Vellei et al., 2017; Maley et al., 2018; Makowiec-Dabrowska et al., 2019).

In panel A of table 1 we regress indicator variables for each of the six trust measures (plus their principal component) on air temperature, T, and the feel factor, F *on the exact day and at the precise location* of the interview. Across all six questions, air temperature on the day of interview does not appear to be strongly associated with reported trust. By contrast, the feel factor, i.e. perceived temperature due to humidity, wind and solar radiation, is strongly and positively associated with distrust. A 1°C increase in perceived temperature due to humidity, wind and solar radiation is associated with a 0.5 to 1 percentage point increase in distrust. The estimates in column 7 suggest a 1°C positive anomaly is associated with an increase in distrust of 0.03 of standard deviation.

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. The parameter estimates for these 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.

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. The parameter estimates confirm this with precisely estimated sizes very close to zero.

[10] We use the first principal component.

3.2 Results: Perceived temperature, trust and polity

In this section we investigate how the association between perceived temperature and distrust varies with the socio-political environment of respondents. The estimates in this section tally well with previous findings on the determinants of trust reported by Alesina and La Ferrara (2002). The parameter estimates in columns 1 and 2 of table 2 show that the link between perceived temperature and distrust is 0.01 of a standard deviation stronger for individuals living in poor dwellings (column 1) and for unemployed respondents (column 2).

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 above the median, the association between perceived temperature and distrust is around 0.03 of a standard deviation stronger.

In columns (4) and (5) of table 2 we use two indices, Government Effectiveness and Rule of Law, to distinguish countries by their perceived quality of governance. The Government Effectiveness Index measures the quality of government policies, its commitment to implementation policies as well as perceptions on the quality of public and civil service and the extent to which public institutions are free from political pressures. The Rule of Law index, in turn, measures the degree of confidence in state institutions, businesses and individuals adhering to the rules of the country. To compute the indices data from 31 globally conducted surveys are used (see Kaufmann et al., 2010 for more details). The parameter estimates indicate that in countries with low Government Effectiveness and Rule of Law indicators, the link between thermal stress and distrust is particularly strong, around 0.3 to 0.4 of a standard deviation stronger than in countries with indices above the median.

We also investigate whether the effect of perceived temperature anomalies varies by baseline trust. For this, we carry out a quantile regression of equation 3. The estimates reported in figure 3 show that effects are relatively stable along the distribution, slightly stronger, however, for individuals with higher levels of trust.

3.3 Results: Individual parts of the heat index algorithm

The advantage of Steadman (1994)'s index is that it collapses four meteorological variables into an easily interpretable number. Whilst its wide use by various meteorological services speaks for its reliability, the heat index's construction remains somewhat discretionary. Accordingly, as a more parsimonious approach we re-estimate equation 3 including all four components as separate covariates. To make the magnitudes comparable, we convert each climatic event into a z-score. The parameter estimates in column (6) of table 2 show that by far the strongest association is between distrust and humidity, which 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.

3.4 Robustness

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

4 Monthly anomalies in perceived temperature and civil unrest

The second part of the paper examines the effect of perceived temperature (measured via the heat index in equation 1) on incidences of civil unrest. We create a panel with one observation per month for each of the 2,757 cells for the years 2009 to 2018. For each cell/month observation we then count the total number of protests and riots and create a dummy, $unrest_{ctm}$, equal to one if cell c experienced at least one incidence of either a riot or a protest in year t and month m and estimate

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

where T_{ctm} and F_{ctm} denote air temperature and the feel factor in cell c in year t and month m. 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 ($\mu_c \times \tau$). In another model, we also include the lagged dependent variable, $riot_{ctm-1}$. We estimate equation 4 by OLS.

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

4.1 Results: Monthly anomalies and civil unrest

Figure 4 consists of three maps showing 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 perceived temperature is particularly high (due to humidity, wind and solar radiation) are more likely to experience more protests and riots.

The parameter estimates based on equation 4 are reported in table 3. Both the air temperature and the feel factor (i.e. perceived temperature due to humidity, wind and solar radiation) are positively associated with incidences of riots or protests, which is robust across different specifications (columns 1 to 3). This association, however, is larger for the feel factor (F), around 0.3 percentage points, than for air temperature (T), around 0.1 percentage point.

In columns (4) and (5) we consider two other dependent variables, strategic and remote violence where strategic developments are events that trigger the onset of violence and remote violence refers to events such as bombings, IED attacks, mortar and missile attacks where the perpetrators did not have to be physically present. Whilst civil unrest is strongly related to attitudes and emotions (Passarelli and Tabellini, 2017), strategic and remote violence are more likely to be determined by tactical and political factors. As such, they should not be determined by perceived temperature, which is what we find with parameter estimates close to zero yet precisely estimated.

4.2 Results: importance of agricultural incomes

Four pieces of evidence all suggest that the effect of perceived temperature highlighted in section 4.1 does not operate through changes in agricultural income.

First, we re-estimate equation 4 with the addition of T and F in the three months before and after month t. Figure 5a reports the parameter estimates for the three leads and lags and shows that the effect operates only through contemporaneous values of perceived temperature. The parameter estimates for all leads and lags are small and precisely estimated. Since it is likely to take a whole agricultural season—around 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 monthly anomalies in perceived temperature along the crop-calendar. The effect of the weather on agricultural productivity and thus agricultural income is considerably stronger during the growing seasons. Combining the two independent data sources outlined in section 2.1 we identify the major crop for each of the 2,757 cells and its growing season. The map in appendix A shows the major crops and is very similar to the one reported by (Harari and La Ferrara, 2018). This information allows us to define a dummy taking the value 1 if month m falls inside the growing season of cell c's major crop. When we interact this dummy with F in column 2 of table 4, we find a a precisely estimated parameter close to zero. This suggests that the effect of F is essentially the same during and outside of the growing seasons of the major cell-specific crop. This finding also points towards income not being a major driver behind the effect of perceived temperature on civil unrest.

Moreover, in figure 5b we group the 12 months of the year into 6 groups according to the month of harvest (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 coefficients show that the effect is remarkably stable along the crop calendar.

Third, in column 4 of table 4 we include all four parts of the heat index separately. As with the estimates in table 2, humidity shows the strongest association with civil unrest. 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 columns 5 and 6 of table 4 show that yearly temperature bears a negative relation to agricultural value added per worker, 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 and precisely estimated.

4.3 Income and direct channel are not mutually exclusive

Whilst the findings in section 4.2 suggest that perceived temperature has an effect on conflict that operates independently of income fluctuations, they do not imply that temperature does not affect conflict through income. This section evaluates the relative importance of both these channels.

[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.

Following the methodology proposed by Harari and La Ferrara (2018), for each cell c in month m we calculate the average air temperature during the growing season *prior to month* m, T_g and include it as an additional regressor in equation 4. If air temperature affects conflict via agricultural incomes, the effect should be captured by the variable T_g.

Column 3 of table 4 shows that a 1°C increase in air temperature in the previous growing season increases incidences of conflict by 0.l3 percentage points. The coefficient on the feel factor, F, in the same month, however, remains large at significant, around 0.5 percentage points. A comparison of the two magnitudes suggests that the effect operating through attitudes and the effect working through agricultural incomes are roughly similar. Moreover, the fact that we find effects for both variables suggests that temperature has two complementing effects on violence: it increases violence by decreasing agricultural incomes and it increases violence by a more direct channel, possibly by decreasing trust.

5 Conclusion

The results presented in this paper suggest that high temperatures as perceived by the human body increase mistrust and incidences of civil unrest in Africa. Whilst climatic fluctuations cannot be changed, these findings nonetheless have a number of policy implications. Our findings highlight the importance of transparent and inclusive policy making by governments across the African continents. The decrease in trust resulting from high temperatures might be mitigated better, if the population does not feel excluded from the policy making process. Transparency appears particularly important in ethnically fragmented societies, where the effect of perceived temperature is stronger. Finally, our results indicate that the effect we highlight in this paper does not exclude the widely documented effect of climatic changes operating via agricultural incomes. The finding that climatic changes can affect economies in different ways is a policy relevant finding.

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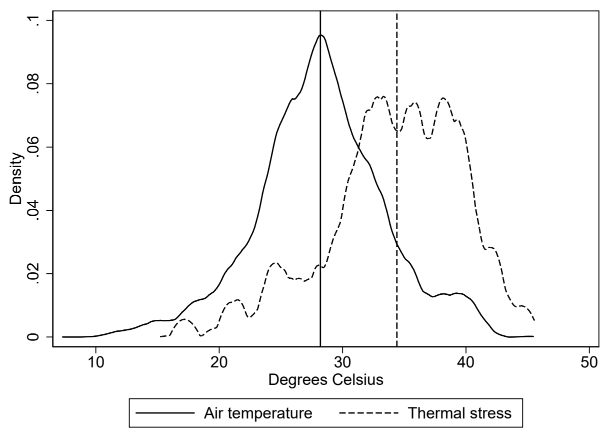
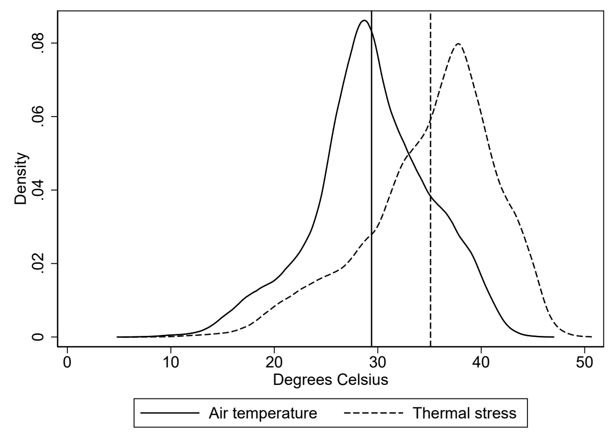
Figures

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

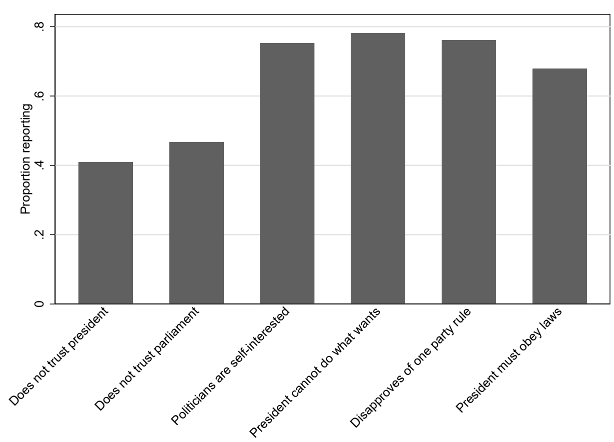
(a) Air temperature and heat index 2014-15



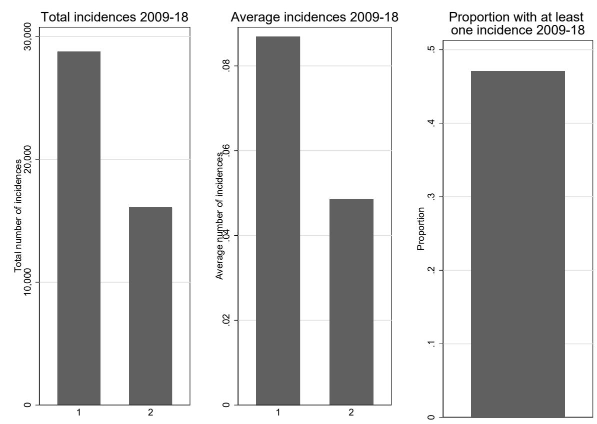
(b) Air temperature and heat index 2009-18



(c) Self-reported trust in government 2014-15

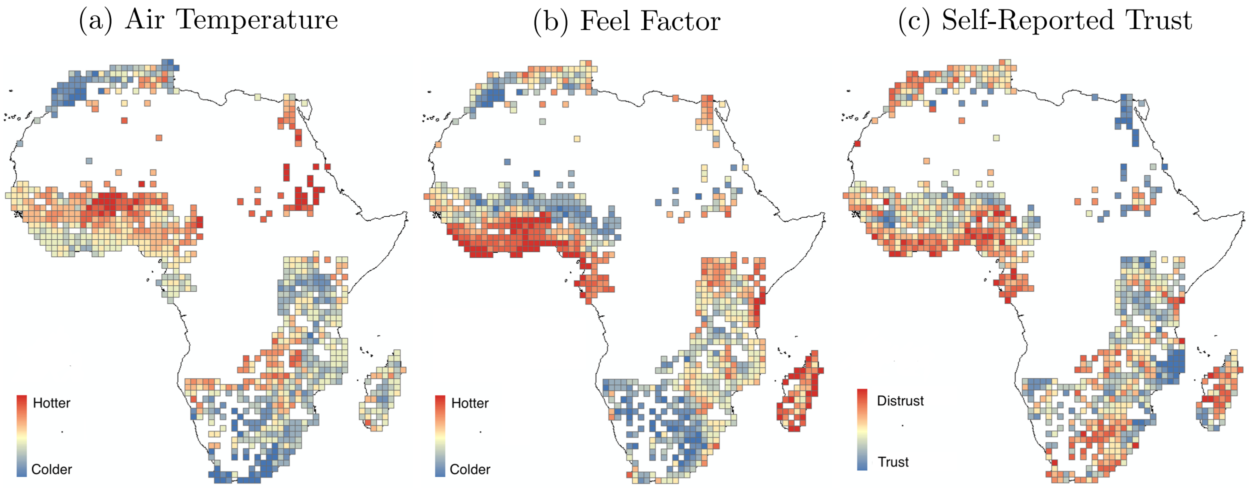


(d) Incidences of protests and riots 2009-14



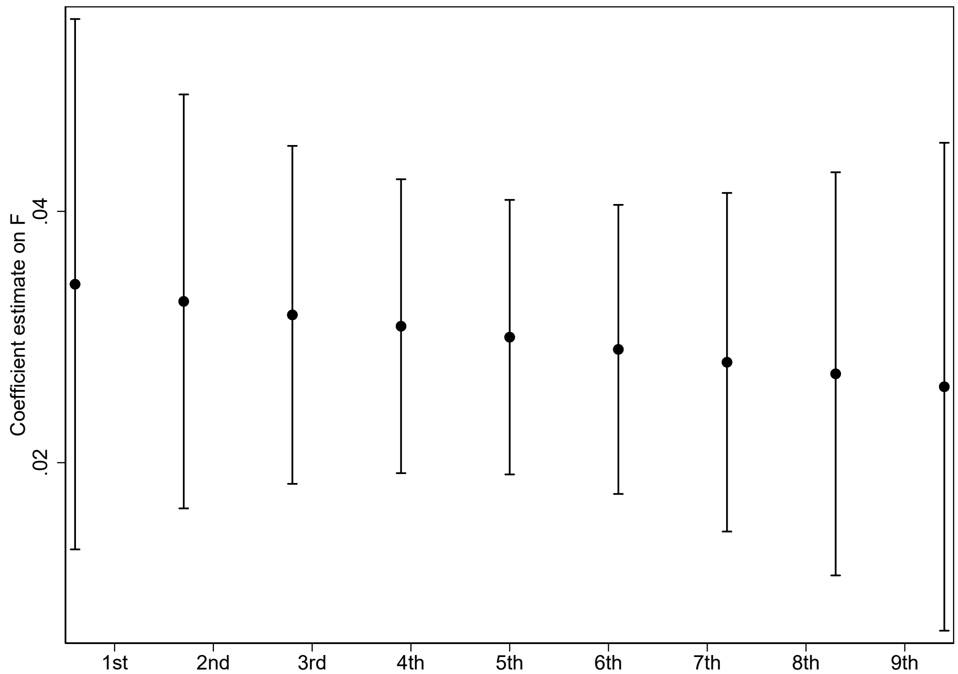
Notes: figures report summary statistics on perceived temperature, trust and civil unrest; panel a reports the air temperature and perceived temperature measured via the heat index in equation 1 in degree Celsius for the Afrobarometer sample for the years 2014 to 2015 panel b reports the air temperature 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 via six questions; 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 reported by Afrobarometer respondents 2014-15, values are based on first principal component of six questions used to measure trust, blue denotes higher trust and red lower trust.

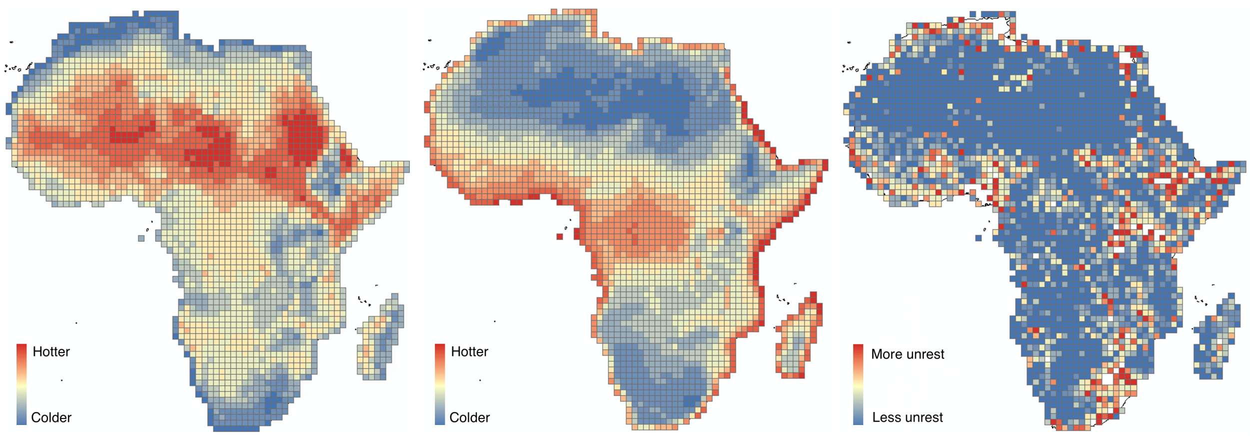
Figure 3: Perceived temperature anomalies - deciles



Notes: figures denotes quantile-regression of self-reported trust on perceived temperature by decile; dependent variable is the z-score of the first principal component of the six measurements for trust; dots represent point estimates for coefficient on *Feel factor (F) on day of interview* (i.e. the perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2) at location and on day of interview; vertical lines denotes 95% confidence intervals; regressions include fixed effects for cell and date of interview and individual characteristics.

Figure 4: Air temperature, perceived temperature and civil unrest in Africa

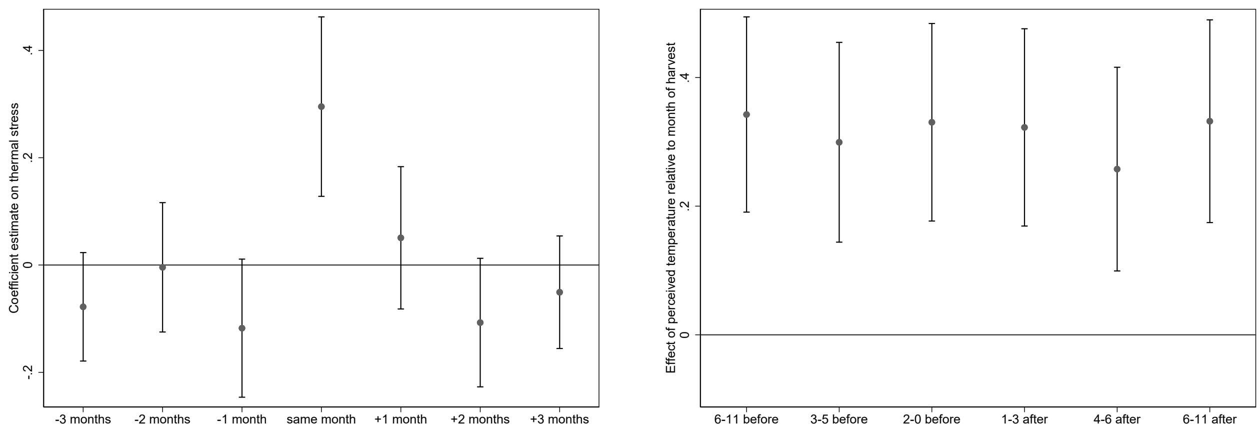
(a) Air Temperature (b) Feel Factor (c) Riots and Protests



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 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) 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 5: Perceived temperature - timing and crop calendar

(a) Effect by month (b) Effect along crop calendar



Notes: figures show the timing of the effect of perceived temperature on incidences of civil unrest; dependent variable takes value 100 if cell c experienced at least one protest or riot in month m; dots denote point estimate for *Feel factor (F) on day of interview* (i.e. perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2) for cell c in month m; vertical lines denote 95% confidence intervals; panel a estimates leads and lags for regressor *Feel factor (F) on day of interview* for the 3 months before and after month m; panel b estimates effect of *Feel factor (F) on day of interview* along the crop calendar for the major crop cultivated in cell c; each dot denotes interaction between *Feel factor (F) on day of interview* and dummies for month m being 6-11 months before, 3-5 months before, 0-2 months before, 1-3 months after, 4-6 months after and 7-11 months after the harvest of the major crop cultivated in cell c; estimates are based on OLS; spatial HAC Conley standard errors with 180km radius and one month lag.

Tables

Table 1: Perceived temperature and trust in government

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variables:			Takes value 100 if respondent				1^{st}
	Trusts in President	Trusts in Parliament	Believes that Politicians are out for themselves	Disapproves of One party rule	Disapproves of President can do what he wants	Believes that President must obey the laws	principal component z-score
			Panel A: Effect of perceived temperature on day of interview				
Feel factor (F) on day of interview	0.832∗∗	1.132∗∗∗	0.799∗∗∗	0.754∗∗∗	0.634∗∗	0.493	0.030∗∗∗
	(0.324)	(0.333)	(0.285)	(0.248)	(0.272)	(0.314)	(0.007)
Air temperature (T) on day of interview	0.232	0.375∗∗	−0.121	−0.022	−0.248∗	−0.226∗	0.002
	(0.172)	(0.157)	(0.123)	(0.106)	(0.137)	(0.133)	(0.004)
			Panel B: Leads and lags for two days before and after interview				
Feel factor (F) on day of interview	0.708∗∗	1.179∗∗∗	0.850∗∗∗	0.598∗∗	0.538∗	0.468	0.028∗∗∗
	(0.356)	(0.367)	(0.316)	(0.280)	(0.314)	(0.336)	(0.008)
Feel factor (F) on:							
Day before interview	−0.271	−0.292	−0.435	0.075	−0.203	−0.043	−0.008
	(0.349)	(0.349)	(0.290)	(0.274)	(0.317)	(0.325)	(0.007)
Two days before interview	0.461	0.292	−0.032	0.177	0.324	0.032	0.008
	(0.339)	(0.344)	(0.323)	(0.268)	(0.304)	(0.322)	(0.007)
Day after interview	0.193	−0.075	0.216	0.271	0.157	−0.195	0.004
	(0.341)	(0.336)	(0.332)	(0.272)	(0.294)	(0.345)	(0.007)
Two days after interview	−0.068	−0.218	0.031	0.060	0.157	0.292	0.000
	(0.361)	(0.353)	(0.303)	(0.271)	(0.306)	(0.333)	(0.007)
			Panel C: Placeboes: 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
Feel factor (F) on day of interview	−0.028	−0.070	−0.096	−0.129	−0.192	−0.160	0.055
	(0.222)	(0.309)	(0.311)	(0.195)	(0.219)	(0.257)	(0.282)
Observations				50,034			
Cell & Date fixed effects	yes	yes	yes	yes	yes	yes	yes
Long term cell average climate	yes	yes	yes	yes	yes	yes	yes

Notes: table shows parameter estimates for regression of self-reported trust on perceived temperature; *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; *Air temperature (T) on day of interview* denotes air temperature at location and on day of interview; Panels A and B: dependent variables take value 100 if respondent does not trust in president (column 1), if respondent does not trust in parliament (column 2), if respondent believes politicians are out for themselves (column 3), if respondent disapproves of one party rule (column 4), if respondent disapproves of president doing what he/she wants (column 5), if respondent believes president should obey the laws (column 6), dependent variable in column 7 is the z-score of the first principal component 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); 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 and trust in government - heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	1^{st} principal component for "trust in government" (z-score)					
Feel factor (F) on day of interview	0.026***	0.024***	0.018**	0.006	0.002	
	(0.007)	(0.007)	(0.009)	(0.014)	(0.014)	
Interaction of Feel factor (F) with						
Respondent is poor	0.010**					
	(0.005)					
Respondent is unemployed		0.010***				
		(0.004)				
Respondent lives in ethnically heterogenous country			0.025**			
			(0.012)			
Respondent lives in country with poor rule of law				0.030**		
				(0.015)		
Respondent lives in country with low government efficiency					0.036**	
					(0.015)	
Climatic event on day of interview						
Air temperature (zscore)						0.004
						(0.020)
Humidity (zscore)						0.110***
						(0.025)
Wind speed (zscore)						0.014
						(0.010)
Solar radiation (zscore)						0.020*
						(0.010)
Rainfall (zscore)						−0.010
						(0.006)
Observations	50,034	50,034	50,034	50,034	50,034	50,034
Cell & Date fixed effects	yes	yes	yes	yes	yes	yes
Long term cell average climate	yes	yes	yes	yes	yes	yes

Notes: table shows parameter estimates for regression of self-reported trust on perceived temperature by individual and country characteristics; 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; *Respondent is poor* = 1 if respondent lives in a shack; *Respondent is unemployed* = 1 if respondent is currently seeking employment; *Respondent lives in ethnically heterogenous country* = 1 if heterogeneity index of country respondent resides in is above the African median; *Respondent lives in country with poor rule of law* = 1 if rule of law polity index for country respondent resides in is below the African median; *Respondent lives in country with low government efficiency* = 1 if government efficiency polity index for country respondent resides in is below the African median; *Air temperature (z-score)* is the z-score of the air temperature at location and on day of interview; *Humidity (z-score)* is the z-score of humidity at location and on day of interview; *Wind speed (z-score)* is the z-score of wind speed at location and on day of interview; *Solar radiation (z-score)* is the z-score of solar radiation at location and on day of interview; *Rainfall (z-score)* is the z-score of precipitation 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 civil unrest

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	= 100 if cell c in month m experiences at least one				
	Riot or protest			Strategic violence	Remote violence
Feel factor (F) in cell c and month m	0.316***	0.330***	0.322***	−0.026	−0.052
	(0.092)	(0.090)	(0.085)	(0.052)	(0.049)
Air temperature (T) in cell c and month m	0.135***	0.093***	0.087***	−0.024	0.043 * *
	(0.033)	(0.032)	(0.030)	(0.018)	(0.017)
Observations	330,840	330,840	330,840	330,840	330,840
Cell, Year & Month fixed effects	yes	yes	yes	yes	yes
Long term cell average climate	yes	yes	yes	yes	yes
Country specific time trend	no	yes	yes	yes	yes
Lagged dependent variable	no	no	yes	yes	yes

Notes: table shows parameter estimates for regression of incidences of civil unrest on perceived temperature; dependent variable in columns 1-3 takes value 100 if cell c experienced at least one protest or riot in month m; dependent variable in column 4 takes value 100 if cell c experienced at least one act of strategic violence in month m; dependent variable in column 5 takes value 100 if cell c experienced at least one act of remote violence in month m; *Feel factor (F) on day of interview* denotes perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2 for cell c in month m; *Air temperature (T) on day of interview* denotes air temperature for cell c in month m; estimates are based on OLS; spatial HAC Conley standard errors with 180km radius and one month lag are reported in parentheses.

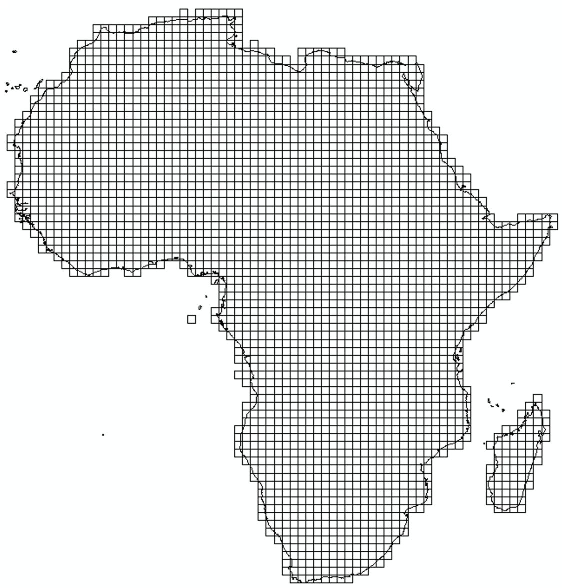
Table 4: Perceived temperature and incidences of civil unrest - mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	= 100 if cell c in month m experiences at least one Protest or riot				Agricultural value added per worker	
Feel factor (F) in cell c and month m	0.279∗∗∗	0.340∗∗∗	0.499∗∗∗		35.51	
	(0.088)	(0.077)	(0.103)		(131.64)	
Air temperature (T) in cell c and month m	0.043 ∗ ∗		0.129∗∗∗		−191.05∗	
	(0.017)		(0.044)		(104.38)	
Feel factor (F) × mixed ethnicity	0.083∗					
	(0.046)					
Feel factor (F) × growing season		−0.044				
		(0.043)				
Temperature in previous growing season			0.343∗∗∗			
			(0.098)			
Climatic event in cell c and month m						
Air temperature (zscore)				0.399 ∗ ∗		−517.79∗
				(0.170)		(301.41)
Humidity (zscore)				1.118∗∗∗		32.76
				(0.262)		(260.0)
Wind speed (zscore)				0.084		−313.09
				(0.119)		(240.43)
Solar radiation (zscore)				0.387 ∗ ∗		−82.66
				(0.195)		(145.88)
Rainfall (zscore)				−0.012		−65.59
				(0.120)		(83.08)
Observations	330,840	330,840	330,840	330,840	404	404
Cell, Year & Month fixed effects	yes	yes	yes	yes		
Country specific time trend	yes	yes	yes	yes		
Long term cell average climate	yes	yes	yes	yes		
Lagged dependent variable	yes	yes	yes	yes	yes	yes
Country fixed effect					yes	yes
Data source	ACLED	ACLED	ACLED	ACLED	World Bank	World Bank

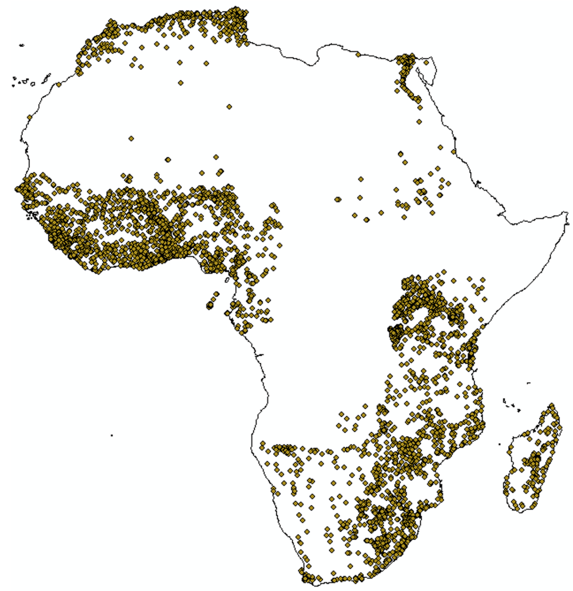
Notes: table shows parameter estimates for regression of incidences of civil unrest and agricultural value added on perceived temperature; dependent variable in columns 1-4 takes value 100 if cell c experienced at least one protest or riot in month m; dependent variable in columns 5-6 is agricultural value added per worker; *Feel factor (F) on day of interview* denotes perceived temperature resulting from humidity, wind and solar radiation outlined in equation 2 for cell c in month m; *Air temperature (T) on day of interview* denotes air temperature for cell c in month m; *Mixed ethnicity* = 1 if cell c contains more than one ethnic homeland; *Growing season* = 1 if month m occurs within the growing season of the major crop cultivated in cell c; *Temperature in previous growing season* is the average air temperature of the growing season preceding month m in cell c; *Air temperature (z-score)* is the z-score of the air temperature in cell c and month m; *Humidity (z-score)* is the z-score of humidity in cell c and month m; *Wind speed (z-score)* is the z-score of wind speed in cell c and month m; *Solar radiation (z-score)* is the z-score of solar radiation in cell c and month m; *Rainfall (z-score)* is the z-score of precipitation in cell c and month m; estimates are based on OLS; spatial HAC Conley standard errors with 180km radius and one month lag are reported in parentheses.

A Additional Maps

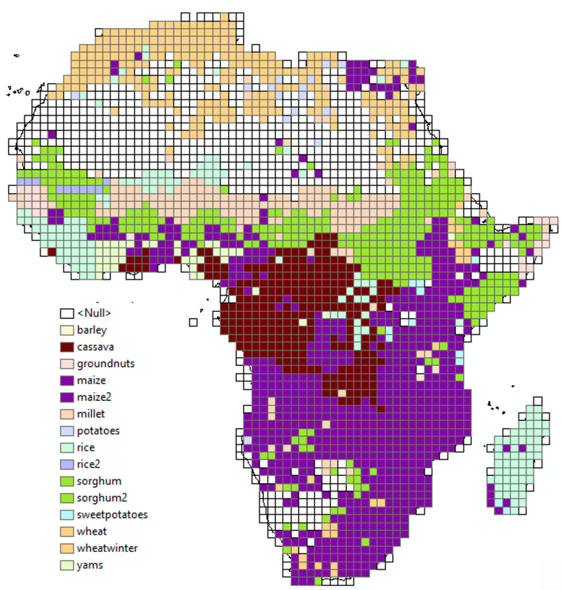
(a) 1×1 arc second grid



(b) Afrobarometer respondents



(c) Major crop areas in Africa



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 5 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 5, we try various combinations of these factors and the results remain remarkably stable across all specifications.

Table 5: 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

The following questions are used to define trust towards the 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*

D Effect of perceived temperature on trust - robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables:		1^{st} principal component				Sum of dummies				1^{st} principal component		
Feel factor (F) on day of interview	0.030∗∗∗	0.025∗∗∗	0.028∗∗∗	0.025∗∗∗	0.046∗∗∗	0.043∗∗∗	0.020∗	0.019 ∗ ∗	0.028∗∗∗	0.025∗∗∗	0.029∗∗∗	0.026∗∗∗
	(0.007)	(0.008)	(0.006)	(0.007)	(0.010)	(0.011)	(0.012)	(0.011)	(0.008)	(0.008)	(0.007)	(0.007)
<u>**Feel factor (F) on:**</u>												
Day before interview		−0.004		−0.003		−0.011		0.001		−0.002		−0.008
		(0.007)		(0.006)		(0.011)		(0.008)		(0.007)		(0.007)
Two days before interview		0.011		−0.004		0.012		−0.008		−0.005		0.008
		(0.007)		(0.007)		(0.011)		(0.010)		(0.007)		(0.007)
Day after interview		0.004		0.006		0.005		0.003		0.005		0.005
		(0.007)		(0.007)		(0.011)		(0.009)		(0.007)		(0.007)
Two days after interview		0.003		0.006		0.002		0.001		0.007		0.002
		(0.007)		(0.007)		(0.011)		(0.009)		(0.008)		(0.007)
Observations							50,034					
Date fixed effects							yes					
Cell by Month fixed effects	yes	yes										
Region by Month fixed effects			yes	yes								
Cell fixed effects					yes	yes					yes	yes
Country fixed effects							yes	yes			yes	yes
Region fixed effects									yes	yes		

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.

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".