Climate change may speed democratic turnover

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The electoral fate of standing politicians depends heavily upon voters' well-being. Might climate change – by amplifying threats to human well-being – cause standing democratic politicians and parties to lose office more frequently? Here I conduct the first-ever investigation of the relationship between temperature, electoral returns, and future climate change. Using data from over 1.5 billion votes in over 4,800 electoral contests held in 19 countries between 1925 and 2011, coupled with meteorological data, I show that annual temperatures above 16°C-21°C (60°F-70°F) markedly decrease officeholders' vote share. I combine these empirical estimates with an ensemble of climate models to project the impact of climate change on the fate of future officeholders. Forecasts indicate that by 2099 climate change may reduce average standing party vote share by over five percentage points in nations with already weak democratic institutions, causing incumbent parties and their politicians to lose office with increasing frequency. These findings indicate that exogenously driven democratic turnover may be the most regular and pervasive potential impact of climate change on political systems.

climate change impacts | democratic stability | elections | voter behaviors

Abbreviations: °C, degrees Celsius; Temp., temperature; SI, supplemental information

Reductions in voter well-being regularly cause democratic politicians to lose office. This is because voters consider their own well-being and the well-being of those around them when deciding how to cast their ballots [1]. When voters are doing well they more frequently vote for their standing politicians [2]. When voters are doing poorly, whether economically or psychologically, they vote for political challengers at higher rates [3]. Importantly, scholars have determined that climate change is likely to undermine future economic [4] and psychological [5] well-being. Might climate change – by reducing citizens' well-being – induce voters to cast out their incumbent politicians at increasing rates in the future?

That diminished voter well-being can produce electoral losses for standing politicians is one of the most extensively documented findings in political science [6]. Most studies focus on the ways that economic outcomes can affect ballot choices, with the conclusion that reductions in macroeconomic performance often precede incumbent politicians' electoral losses [7, 8, 9, 10, 11, 12]. Tufte (1978) articulated this relationship as a basic principle of politics: "When you think of economics, think elections; when you think of elections, think economics" [13]. Yet, alterations in well-being not directly tied to the formal economy can also shape voter behaviors. Harmful events such as hurricanes [14, 15], tornadoes [16], floods [17, 18, 19], and droughts [20, 21, 22] have also shaped the outcome of historical electoral contests. Even more minor reductions in psychological well-being, such as the loss of a favored sports team, have been linked to fewer ballots cast for standing politicians [23].

Climate change induced warming is likely to reduce future economic well-being [24, 25, 26] in both rich [4, 27] and poor [28] countries, in part by reducing individual productivity [29], and is likely to amplify the incidence and severity of extreme weather events [30, 31, 32]. Future warming may also undermine human psychological well-being through mechanisms directly tied to increases in temperature extremes, such as worsened emotional states [33, 34]. These projected impacts of global climate change include many of the exact weather and

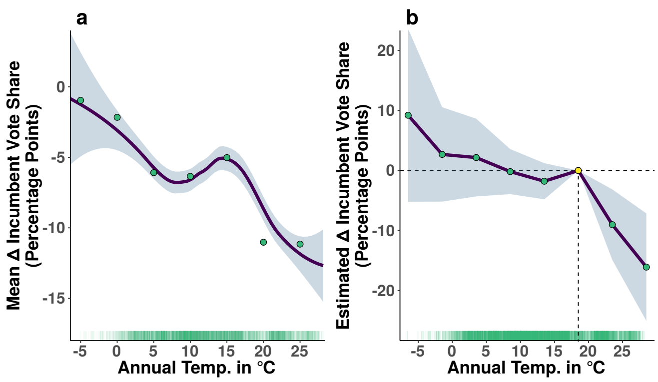

Fig. 1. *Incumbent party vote share declines with increases in annual temperature.* **Panel (a) depicts the relationship between average annual temperature and changes in the constituency-level vote share of national lower house incumbent politicians from 1,256 constituencies across 19 countries between 1925 and 2011. Points represent the average change in incumbent vote share for each 5°C annual temperature bin. The line represents a loess smoothing of the raw data. Panel (b) draws from the estimation of the fixed effects model in Equation 1 and plots the predicted change in vote share associated with each 5°C temperature bin. As annual temperature increases beyond 16-21°C (60-70°F), changes to incumbent vote share become markedly negative. Shaded error bounds represent 95% confidence intervals.**

Significance

Scholars have examined the possible extreme political consequences of climate change such as increased civil conflict, violent protest, and state failure. However, most political and policy change does not arise through violence; instead, change most often arises via elections. Before citizens rebel, they protest. Before they protest – at least in democracies – they vote. Here I explore how voters might respond to the likely impacts of climate change. I find that hotter annual temperatures decrease the vote share of standing parties, amplifying their probability of electoral loss. Model forecasts indicate that unmitigated climate change may speed democratic turnover in the future. These added political threats may shorten parties' electoral time-horizons, magnifying the political difficulty of implementing long-run climate adaptation and mitigation policies.

Reserved for Publication Footnotes

climate-induced stressors that have historically caused incumbent democratic politicians to lose votes. Thus, a changing climate may indeed induce citizens to cast out their incumbent politicians with increasing rapidity. Yet, while this hypothesis flows readily from over a century of literature, this study is the first to explore it.

Here I conduct a multi-national investigation of the relationship between historical temperatures and constituency-level electoral outcomes and link these findings to predictions of future climatic changes. I examine four questions. First, have exogenous increases in temperature harmed the historical vote share of officeholding democratic parties? Second, do the effects of hotter temperatures vary by level of economic development or by density of agriculture? Third, might climate change alter constituency-level vote share in the future? Finally, which countries may see the highest future increases in warming-induced democratic turnover?

Temperature and Changes to Incumbent Vote Share

To investigate if hotter temperatures have indeed reduced historical incumbent party vote share, I employ a dataset of constituency-level electoral returns based on over 1.5 billion votes cast in over 4,800 electoral contests held in 19 countries between 1925 and 2011 [35]. I link these data to constituency spatial boundaries to map historical monthly meteorological conditions onto each electoral constituency [36] (see *Supplemental Information (SI): Data Description* and *SI: Map of Constituency Boundaries*). The theoretical relationship of interest is the total causal effect of constituency-level average annual temperature in the year prior to an election on changes in the vote share of major incumbent party politicians. I empirically model this relationship as:

$$\Delta Y_{it} = f(temp_{it}) + precip_{it} + \alpha_i + \zeta_m + \gamma_t + \nu_{jt} + \epsilon_{it} \quad [1]$$

I control for precipitation ($precip_{it}$) as it is correlated with temperature but could independently cause changes in voter behaviors [37] (though excluding precipitation does not notably alter parameter estimates, see *SI: Main Effect*). In this time-series cross-sectional model, i indexes electoral constituencies, j indexes countries, m indexes election months, and t indexes election years. ΔY_{it} represents the change in vote share of the incumbent party ($Y_{it} - Y_{it-1}$), defined as the party that won the plurality of votes in that constituency in the prior election [38]. Taking this first difference removes from the data potentially confounding secular factors – like strength of incumbent party – that may evolve incrementally in each electoral constituency over time [4].

The main independent variable of interest, $temp_{it}$, represents the average temperature over the twelve months prior to an election held in month m for constituency i in country j and year t (see *SI: Temperature and Precipitation*). The relationship of interest is represented by $f()$, which I implement empirically using indicator variables for each 5°C annual temperature bin, allowing for flexible estimation of a non-linear relationship [39, 29] between temperature and alterations in incumbent party vote share (the functional form remains similar across the use of 2°C or 1°C temperature bins, see *SI: Alternative Temperature Bins*).

Unobserved geographic or temporal factors may influence electoral outcomes in a way that correlates with temperature. For example, voters may be better off on average in constituencies that have better legal institutions, in certain months of the year, or in years with better global economic performance. To ensure that these factors do not bias estimates of the effect

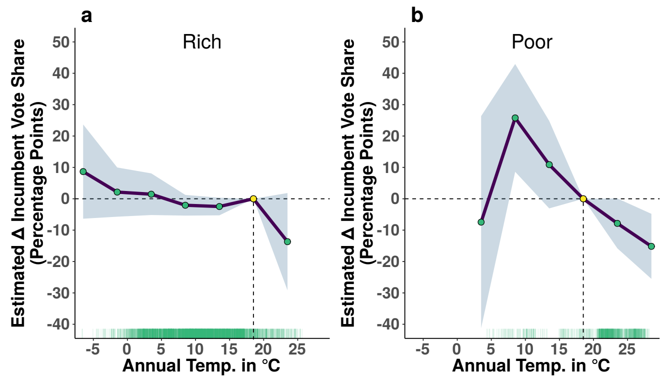

Fig. 2. ***Hot temperatures produce declines in incumbent vote share in both rich and poor countries.*** **Panel (a) plots the predicted changes in incumbent party vote share associated with estimating Equation 1 on the sample of above-median income countries in the data and panel (b) plots this relationship for constituencies in countries falling below median income [4]. Past 21°C, changes in incumbent vote share again decline for both, though rich country declines are significant only at the p<0.10 level. Shaded error bounds represent 95% confidence intervals.**

of temperature on incumbent party vote share, I include in Equation 1 three terms, α_i, ζ_m, and γ_t, that represent constituency, electoral month, and calendar year of election indicator variables, respectively. These variables control for all constant unobserved characteristics for each constituency and for each election month and year [40]. Further, there may be unobserved, country-specific factors that influence changes in political outcomes over time [4]. In order to control for these potential confounds I include ν_{jt} in Equation 1, representing country-specific year indicator variables (results are robust to the use of continent-specific year indicators instead, see *SI: Time and Location Controls*). The identifying assumption, consistent with the literature [41], is that annual temperature is as good as random after conditioning on these fixed effects. The estimated model coefficients on temperature terms can thus be interpreted as the causal effect of temperature on changes in incumbent vote share [4, 41, 39, 42].

I adjust for within-constituency and within-year correlation in ϵ_{it} by employing heteroskedasticity-robust standard errors clustered on both constituency and year [43] (the results are also robust to accounting for spatial and serial dependence [44, 45], see *SI: Spatial and Serial Correlation*). I exclude non-climatic control variables from Equation 1 because of their potential to generate bias – a phenomenon known as a 'bad control' [4, 42] – in the parameters of interest. Because of heterogeneous constituency sizes, I weight the regression in Equation 1 by the number of votes cast in each constituency election. Finally, I omit the 16°C-21°C (60-70°F) temperature indicator variable when estimating Equation 1. This range contains as its midpoint the average temperature associated with optimal well-being (65°F) [46]. I thus interpret the parameter estimates of $f(temp_{it})$ as the change in incumbent party vote share associated with a particular temperature range relative to this baseline category.

The results of estimating Equation 1 for the effects of temperature on changes to incumbent party vote share indicate that after controlling for time, location, and country-specific trends, annual temperatures above 21°C (70°F) significantly reduce incumbents' electoral performance (see Figure 1, panel (b) and *SI: Regression Tables* for full estimation results). For

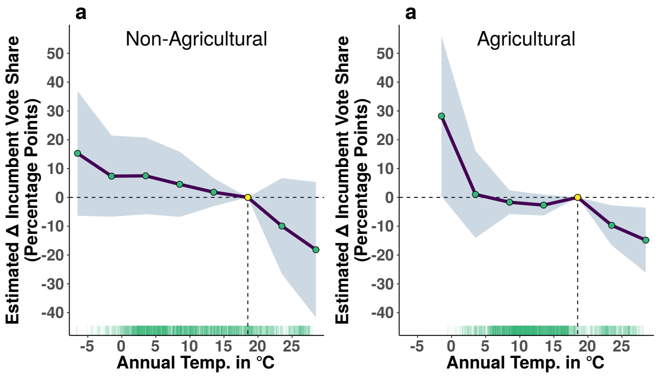

Fig. 3. ***Increases in temperature produce declines in incumbent vote share in both non-agricultural and agricultural constituencies.*** **Panel (a) plots the predicted changes in incumbent party vote share associated with estimating Equation 1 on the sample of constituencies with below-median percentage of remote-sensed agricultural croplands and panel (b) plots this relationship for constituencies with above-median percentages of crop cover. As temperatures increase across both, changes in incumbent vote share decrease. Past 21°C, changes in incumbent vote share decline for both, though these declines in non-agricultural constituencies fail to gain significance at standard thresholds. Shaded error bounds represent 95% confidence intervals.**

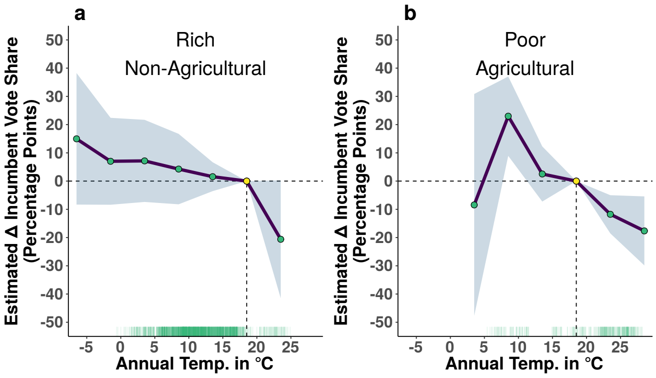

Fig. 4. ***Rich country non-agricultural and poor country agricultural constituencies show large electoral effects of temperatures.*** **Panel (a) plots the predicted changes in incumbent party vote share associated with estimating Equation 1 on the sample of rich country constituencies with below-median percentage of remote-sensed agricultural croplands and panel (b) plots this relationship for poor country constituencies with above-median percentages of crop cover. Vote share in rich non-agricultural areas displays a significant reduction in incumbent vote share in response to increases in annual temperature above 21°C, though this result is only significant at the p<0.10 level. Poor country agricultural constituencies also exhibit marked alterations in vote share in response to shifts in temperatures, significant at standard thresholds. Shaded error bounds represent 95% confidence intervals.**

example, annual temperatures in the range of 21°C-26°C reduce incumbent vote share by over nine percentage points relative to the 16°C-21°C baseline (coefficient: −9.024, p: 0.003, n: 4,880) while constituency annual temperatures above 26°C reduce incumbent vote share by over sixteen percentage points (coefficient: −16.100, p<0.001, n: 4,880) (of note, these results remain highly significant even after Bonferroni correction for each temperature bin included in the regression [47], see *SI: Bonferroni Correction*).

A 5°C increase in temperature – the average increase predicted under the RCP8.5 scenario for 2099 as compared to 2010 – that produced a reduction in incumbent vote share of over nine percentage points could be politically substantial. Examining the constituencies in the 16°C-21°C temperature range indicates that 31% of historical elections had parties that won by less than this nine point margin. In two party constituencies in this range – where electoral swings are mechanically equal to twice the reduction in incumbent vote share – 41% of historical elections would have been altered by a nine percentage point reduction in the winning party vote share. Thus, the effects of hotter annual temperatures on changes in vote share are of a magnitude that is highly politically meaningful and would have resulted in substantial alterations to the historical democratic process if applied to past electoral returns (see *SI: Frequency of Close Elections*).

Income and Agriculture

The above estimates represent the average effect of temperatures on changes to incumbent party vote share across all constituencies in the sample. However, democratic constituencies may vary in their response to increasing temperatures. For example, politicians and voters in rich countries may be better able to respond and adapt to the social stressors associated with hotter temperatures, while politicians and voters in poor countries may lack the resources needed to smooth temperature shocks and thus experience more notable decreases in well-being [28, 4]. Moreover, not all voters in rich or poor countries are likely to be equally affected by the costs of exposure to hotter temperatures. For example, voters in agricultural areas may experience more direct and costly effects of hotter annual temperatures than do voters in areas less reliant on agriculture for their overall well-being [4, 48]. This leads to the second question, do the effects of hotter temperatures vary by level of economic development or by density of agriculture?

To examine whether richer or poorer countries' voters are more sensitive to amplifications in temperature, I stratify the sample by median country-level incomes (measured in per-capita purchasing power parity units) and estimate Equation 1 for both rich and poor country subsamples [41, 4]. Figure 2, panel (a), shows that the effect of annual temperatures greater than 21°C on changes to incumbent party vote share in rich country constituencies is negative, though this effect is significant only at the p<0.10 level (coefficient: −13.677, p: 0.084, n: 3,933). Panel (b) of figure 2 shows that the effect of annual temperatures greater than 26°C on changes to incumbent party vote share in poor country constituencies is also negative and is highly statistically significant (coefficient: −15.162, p: 0.004, n: 947). Thus both in richer and poorer countries I find evidence indicating declines in incumbent party vote share due to an increase in temperature above 21°C, suggesting that higher incomes may not substantially mute the impact of warming on electoral outcomes (see *SI: Rich and Poor*). This is consistent with the observation that increasing temperatures reduce economic well-being in both rich and poor nations [4, 27, 28].

Using data on remote-sensed crop-cover [49] to split constituencies along the median of percent of croplands, I repeat the above procedure to examine whether agricultural constituencies demonstrate differential electoral responses to increasing temperatures as compared to non-agricultural constituencies (see *SI: Agricultural and Non-Agricultural*). Figure 3, panel (a), shows that the effect of annual temperatures

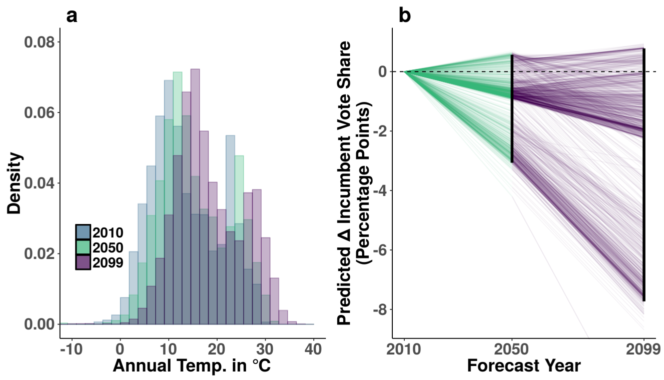

Fig. 5. *Climate change may speed democratic turnover via reductions in incumbent vote share.* **Panel (a) depicts the distributions of annual temperature calculated from 21 downscaled climate models for the constituencies in the sample in 2010, 2050, and 2099. Annual temperatures increase in both magnitude and variation by 2050 and 2099 as compared to 2010. Panel (b) depicts the constituency-level forecasts for the impact of climate change on alterations in incumbent vote share in the future. To incorporate downscaled climate model uncertainty, I calculate an estimated change for an ensemble of 21 climatic models for each of the 1,256 constituencies, producing 26,376 estimates for both 2050 and 2099. I take the constituency average of these estimates, plotting the change between 2010 and 2050 with green lines and the predicted change between 2050 and 2099 with purple lines. The black vertical lines indicate the 2.5th to 97.5th percentile range across the average constituency estimates. As can be seen, currently hotter constituencies are predicted to experience markedly steeper negative changes to incumbent party vote share.**

greater than 26°C on changes to incumbent party vote share in non-agricultural constituencies is markedly negative, though this effect is estimated with higher variance and fails to gain significance at standard thresholds (coefficient: -18.175, p: 0.130, n: 2,281). Panel (b) of figure 3 shows that this effect in agricultural constituencies is also negative and is statistically significant (coefficient: -14.847, p: 0.010, n: 2,271). Thus both agricultural and non-agricultural constituencies' coefficient estimates suggest a decline in incumbent party vote share due to an increase in temperature above 21°C. These findings are consistent with the observation that increasing temperatures reduce both agricultural and non-agricultural economic growth [4].

Combining these insights, I split the sample along rich and poor countries' agricultural and non-agricultural constituencies and estimate Equation 1 in each sub-sample (see *SI: Income and Agriculture*). Figure 3, panel (a), shows that the effect of annual temperatures greater than 21°C on changes to incumbent party vote share in rich country non-agricultural constituencies is negative, though this effect is significant only at the $p<0.10$ level (coefficient: -20.604, p: 0.053, n: 2,006). Panel (b) of figure 3 shows that this effect in poor country agricultural constituencies is also negative and is highly statistically significant (coefficient: -11.760, $p<0.001$, n: 344). The regression models suggest the decline in incumbent party vote share due to an increase in temperature above 21°C is thus driven primarily by non-agricultural constituencies in rich nations and by agricultural constituencies in poor nations. These results may implicate differential causal political mechanisms underlying the relationship between temperature and vote shares in rich versus poor nations and suggest an important area for future research.

Constituency Forecast

The historical data indicate that past temperatures have likely altered historical electoral outcomes in meaningful ways. Further, climate change is likely to produce positive shifts in annual temperature distributions in the future [50] (see Figure 5, panel (a)). Positive shifts in annual temperatures above 21°C may acutely reduce incumbent party vote share in the future, increasing the rate at which incumbent democratic parties and their politicians lose office. These facts lead to the third question: might climate change alter constituency-level vote share in the future?

To examine this question, I calculate projected average annual temperatures for 2050 and 2099 from NASA Earth Exchange's (NEX) bias-corrected, statistically downscaled temperature forecasts drawn from 21 of the CMIP-5 ensemble models run on the RCP8.5 emissions scenario (see *SI: Climate Model Data*). I couple these predicted temperatures with the historical estimate of the relationship between annual temperatures and changes in incumbent party vote share – employing a spline regression model that closely matches the results from Equation 1 – to calculate a forecast of possible alterations in future vote share due to climate change for each constituency across each downscaled climate model (see *SI: Constituency-Level Forecast*).

I define the constituency-level forecast of the predicted change in incumbent party vote share due to climate change by 2050 (V_{i2050}) as:

$$V_{i2050} = \overline{\Delta\hat{Y}_{ki2050} - \Delta\hat{Y}_{ki2010}} \qquad [2]$$

and for the change from 2010 to 2099 (V_{i2099}) as:

$$V_{i2099} = \overline{\Delta\hat{Y}_{ki2099} - \Delta\hat{Y}_{ki2010}} \qquad [3]$$

Where k indexes the 21 specific climate models and i indexes the constituencies. Further, $\Delta\hat{Y}_{ki}$ represents the fitted values derived from the a spline fit of the downscaled climate model data using the functional form from the estimated parameters of Equation 1 for 2050 and 2099 (see *SI: Main Forecast Model*). Of note, the results remain similar under the use of the fitted values from Equation 1 directly (see *SI: Alternative Forecast Model*). Using a full ensemble of climate models allows for incorporating uncertainty regarding the underlying climatic forecasts into the change in incumbent vote share predictions [39, 41].

Figure 5 panel (b) plots the forecast results. Each of the 1,256 constituencies in the sample has a mean prediction across all of the 21 downscaled climate models. The first quartile predicted reduction in incumbent vote share by 2099 is -5.8 percentage points while the median reduction is -1.9. Constituencies with higher historical annual temperatures experience the largest predicted future declines in incumbent vote share while cooler constituencies may experience more mild declines to even slight increases in vote share. However, the predicted negative impacts of climate change are over thirteen times greater in magnitude than are the positive impacts (the maximum mean prediction by 2099 among sample constituencies is 0.95 percentage points while the minimum mean prediction is -12.43 percentage points).

Country Forecast

Some nations are hotter than others on average. This fact, coupled with the observation that the effects of temperature

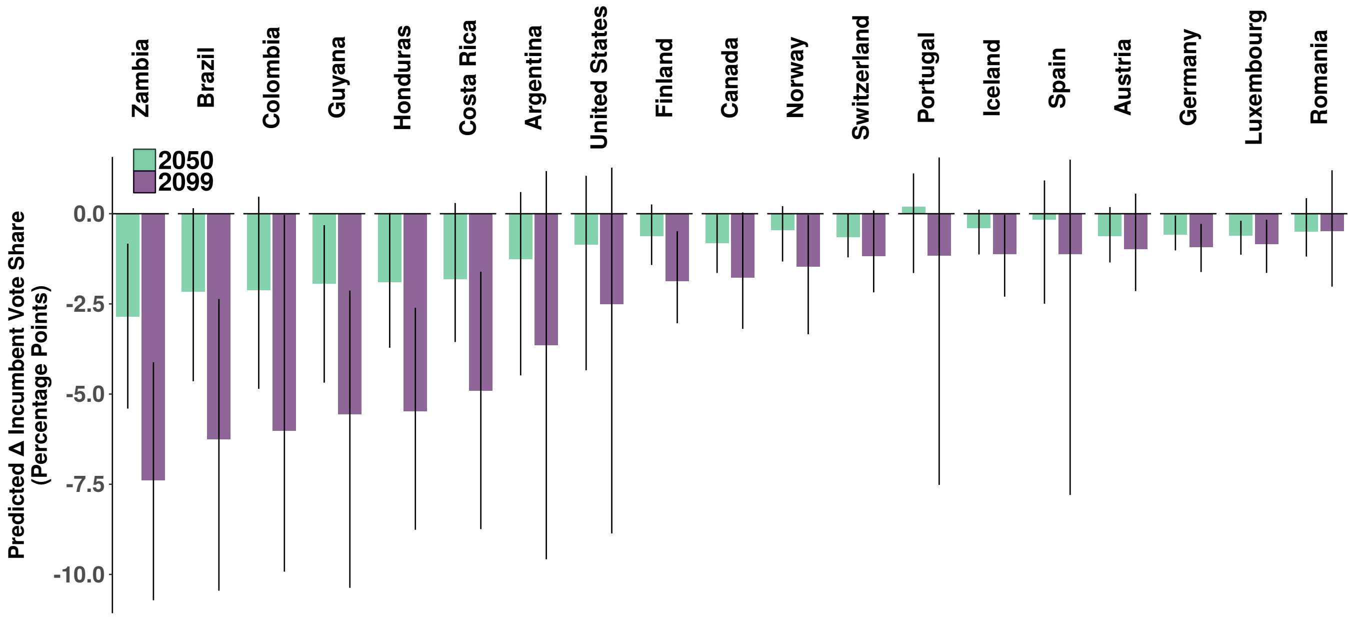

Fig. 6. ***Climate change may increase the frequency of democratic turnover most in warmer, poorer nations.*** **This figure depicts the country-level averages across the 26,376 constituency-level climate model forecasts for the impact of climate change on alterations to future incumbent vote share by 2050 and 2099. As can be seen, countries with constituencies that experience presently hotter annual temperatures – countries that include many of the poorest countries in the sample – are likely to experience the greatest climate-induced increase in democratic turnover. To incorporate both downscaled climate model uncertainty and intra-country variance, I present the 2.5th to 97.5th percentile range of the 21 climate models across each country's set of constituencies via the black vertical lines. Countries with greater intra-country variance in historical annual temperatures, like the United States, have a larger range of future constituency-level predictions.**

on changes to incumbent vote share are non-linear, with most acute effects observed at higher temperatures, leads to the fourth question: which countries may see the highest future increases in warming-induced democratic turnover?

Figure 6 plots country-level forecast results for 2050 and 2099, respectively. Bars for each country represent the average prediction across all of the 21 climate models across each of the constituencies within that country (see *SI: Country-Level Forecast*). Countries that have higher spatial variation in annual temperatures – such as the United States and Argentina – have a higher range of underlying constituency forecasts. Importantly, countries with higher average historical temperatures – such as Zambia, Brazil, and Colombia – may experience the most significant future reductions in incumbent vote share.

Discussion

Voting is central to modern politics. It provides the primary means of democratic participation, shapes politicians' incentives, and regulates the nature of policies. The available evidence indicates that climate change may alter voting patterns in the future, increasing incumbent electoral losses and speeding rates of democratic turnover.

There are several considerations important to the interpretation of these results. First, while I have data from over a billion votes cast across more than a thousand constituencies, optimal data would also include countries not within the present sample. Of special import would be countries with high average annual temperatures, like those in Sub-Saharan Africa. The lack of available spatial data on such countries' historical electoral boundaries limits the current sample. Second, because I spatially average temperature and precipitation values to the constituency-level, measurement error may exist between average climatic conditions and those that voters actually experienced, possibly attenuating the estimated magnitude of the effects [51]. Third, these estimates are based exclusively on annual temperature and precipitation. Because climate change is likely to increase extreme weather events like tornadoes [52], and because such events can also reduce incumbent vote share [16], these results may underestimate the full impact of climate change on future democratic turnover. Finally, it is possible that voters may adapt to altered future climates with political behaviors not seen in the historical data.

Ultimately, turnover – when directly related to politician performance – is vital to well-functioning democracy [53]. However, the empirical results I present here indicate that democratic turnover might increase as a result of climatic events outside the control of individual politicians. This exogenously driven political turnover may shorten democratic time horizons, inducing parties and their politicians to focus on short-run policies at the expense of important longer-run strategies [54]. This pattern may have a particularly deleterious impact on climate mitigation, as its long-run benefits are unlikely to be observed from one election to the next. Moreover, the uncertainty induced by increasing rates of democratic turnover can directly upset macroeconomic outcomes [55, 56]. Even more starkly, turnover in nations with weak democratic institutions can upend political stability. If incumbents in weak democracies foresee a greater risk of losing office, they sometimes employ electoral fraud and pre-electoral violence to maintain power [57, 58]. If these methods fail, incumbents' loss occasionally precipitates post-electoral violence that can in turn induce broader civil conflict [59, 60]. These insights, when coupled with the empirical findings above, suggest climate change may alter the nature of democratic politics in costly ways in the future.

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Climate change may speed democratic turnover

Supplemental Information

Nick Obradovich

Contents

Map of Constituency Boundaries

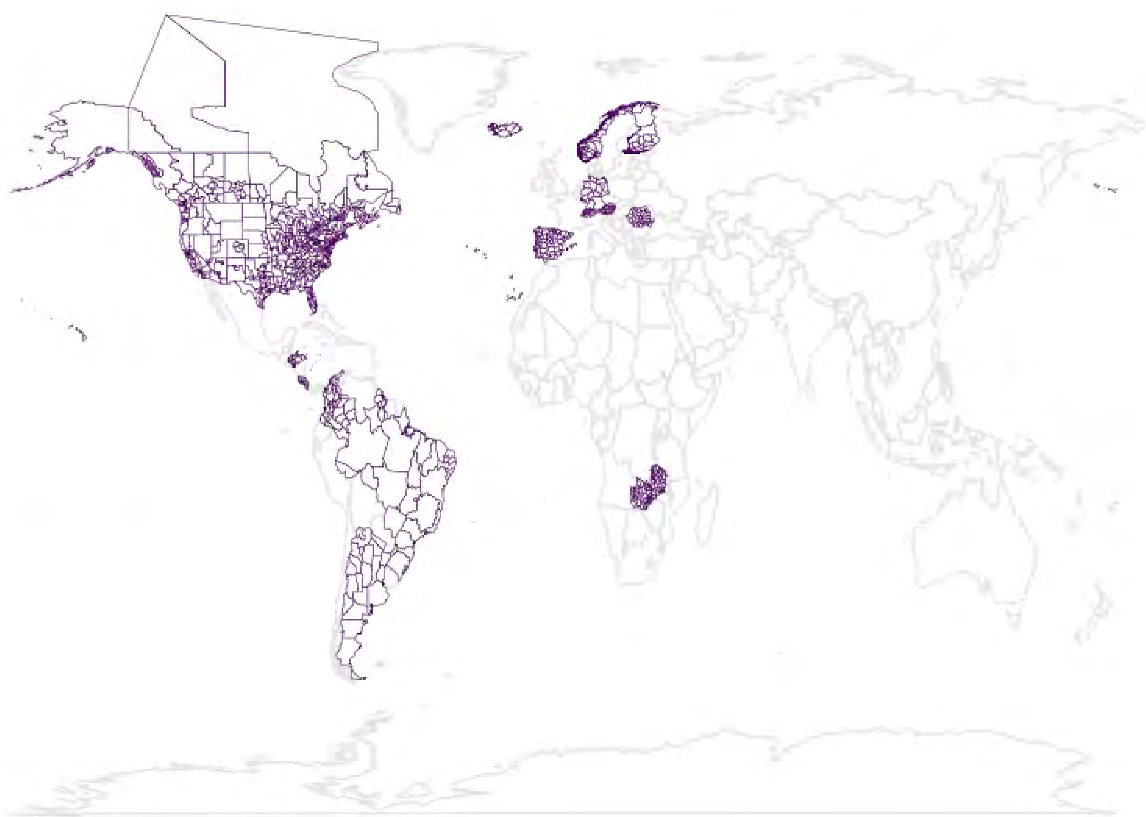

Figure S1: Plot of Constituency Boundaries. The constituencies included in the analysis have broad coverage across 19 countries, with unbalanced temporal coverage from 1925-2011.

Figure S1 displays the constituency boundaries included in the analysis.

Data Description

Political Variables

I obtain constituency level electoral data from the Constituency Level Electoral Archive (CLEA). This is the most comprehensive global archive of constituency level historical electoral returns for countries' national lower house. For each constituency within each country, the archive lists the month and year in which that election occurred. It also lists, for each party, the basis of the primary dependent variable: the party share of the constituency vote total. The dataset can be obtained here and the codebook can be obtained here.

In order to map climatic data onto political variables, one needs a broad set of spatial electoral district boundaries. Until recently this was unavailable. A new product, the Geo-Referenced Electoral Database

(GRED) has been released by the same researchers that produce CLEA. The GRED data represent – by far – the most comprehensive publicly accessible database of constituency spatial boundaries.

The GRED data contain a cross-sectional snapshot of constituency level electoral boundaries for a given country-year. Unfortunately, electoral boundaries change over time. Thus for any given country, the boundaries in GRED may be valid for only one election, for only a few elections, or, in some cases, for all of a country's elections. To determine which boundaries were valid for which country-years, I consulted the constituency boundary history for each country in the GRED data, keeping only those elections from CLEA for which the GRED boundaries are valid. The GRED data can be accessed here.

CLEA data provides the share of the constituency vote total for each party running in a country's lower-house national legislative elections. The main dependent variable is the change in constituency vote share (from $t-1$) in election t of the party that won the majority of that constituency's vote in election $t-1$. This approach is consistent with previous literature that incorporates data from multiple electoral systems[1].

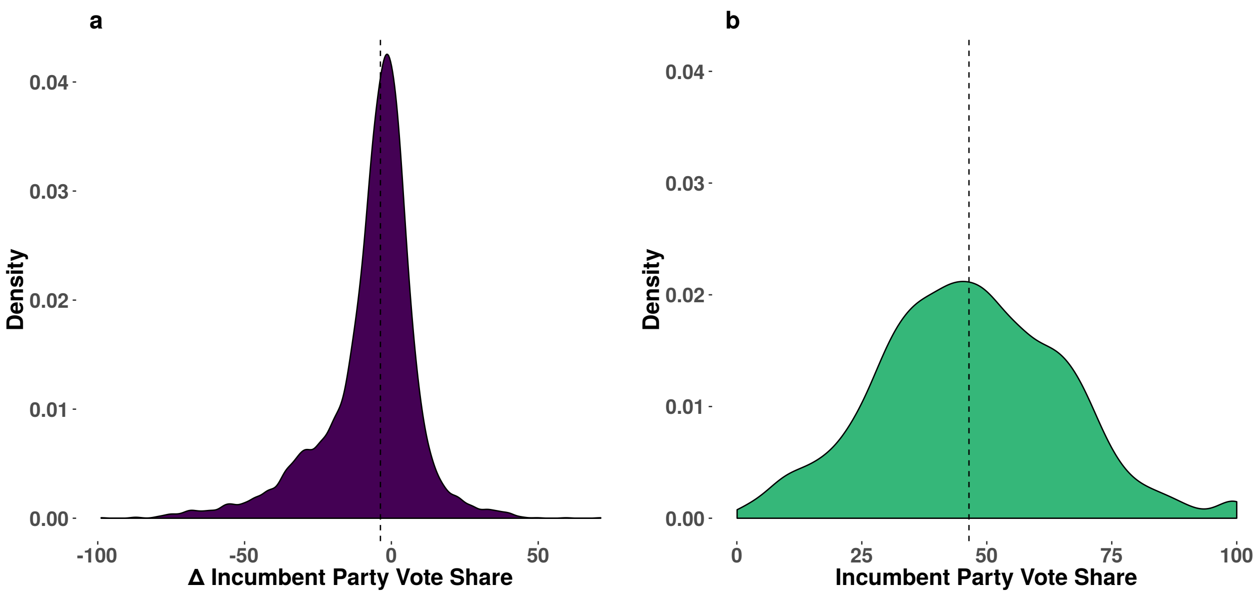

Figure S2: Density plot of changes to major incumbent party constituency vote share and level of incumbent party vote share. Dashed lines represent medians of the respective distributions.

Most elections in the data are relatively competitive (the median major incumbent party vote share across constituencies is 46%). This can be seen in Figure S2, panel (b). The median change in incumbent party vote share is -4 percentage points.

Election Years, Constituencies, and Votes

Because of the nature of electoral boundaries that regularly change in some countries and remain relatively fixed in others, the electoral boundary data enables use of longer periods of elections for some countries and shorter periods for others. Of additional note, because a year of data must be used in order to calculate constituency-level incumbents from the first period, I lose the first year of each new electoral boundary to calculating the dependent variable. Table S1 displays the number of years that each country enters the sample.

Further, constituencies vary in geographic size across countries. Some countries, like the United States, use smaller districts for their lower house elections than do other countries, like Brazil, who use larger geographic units. Table S1 also displays the number of unique constituencies that enter the sample for each country.

Table S1: Sample Details

Country	Years	Constituencies	Obs.	Total Votes
Canada	3	308	739	3.441e+07
Colombia	3	33	83	2.413e+07
Costa Rica	14	7	98	1.437e+07
Finland	13	15	166	3.073e+07
Germany	5	16	56	1.743e+08
Argentina	9	24	110	8.213e+07
Guyana	5	10	30	587520
Honduras	6	18	108	2.572e+07
Iceland	10	8	88	1.351e+06
Austria	5	43	173	1.924e+07
Luxembourg	17	4	53	3.304e+07
Norway	15	19	285	3.368e+07
Portugal	12	20	197	5.42e+07
Romania	3	41	62	1.695e+07
Spain	10	52	465	1.984e+08
Switzerland	3	26	66	5.275e+06
Brazil	5	27	128	3.6e+08
United States	5	435	1645	3.878e+08
Zambia	3	150	328	3.877e+06

Temperature and Precipitation

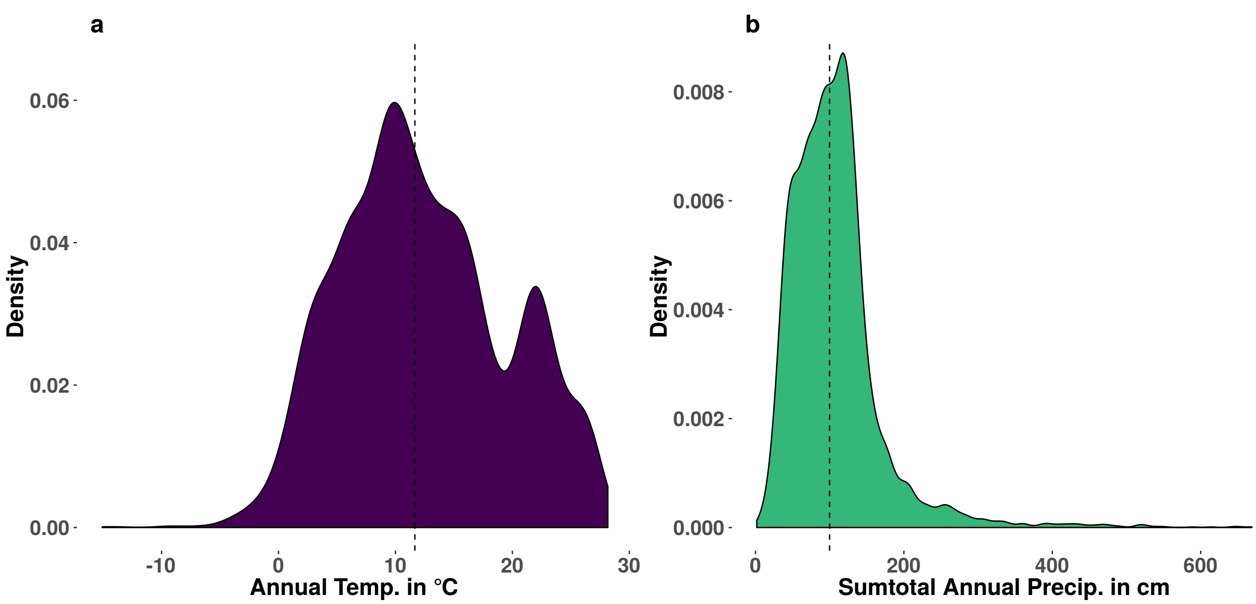

Figure S3: Density plots of annual temperature and precipitation variables.

CRU Meteorological Data

I employ the gridded global temperature and precipitation data produced by the Climatic Research Unit (CRU)[2]. This is one of the most frequently utilized datasets in the economic and social analysis of the impacts

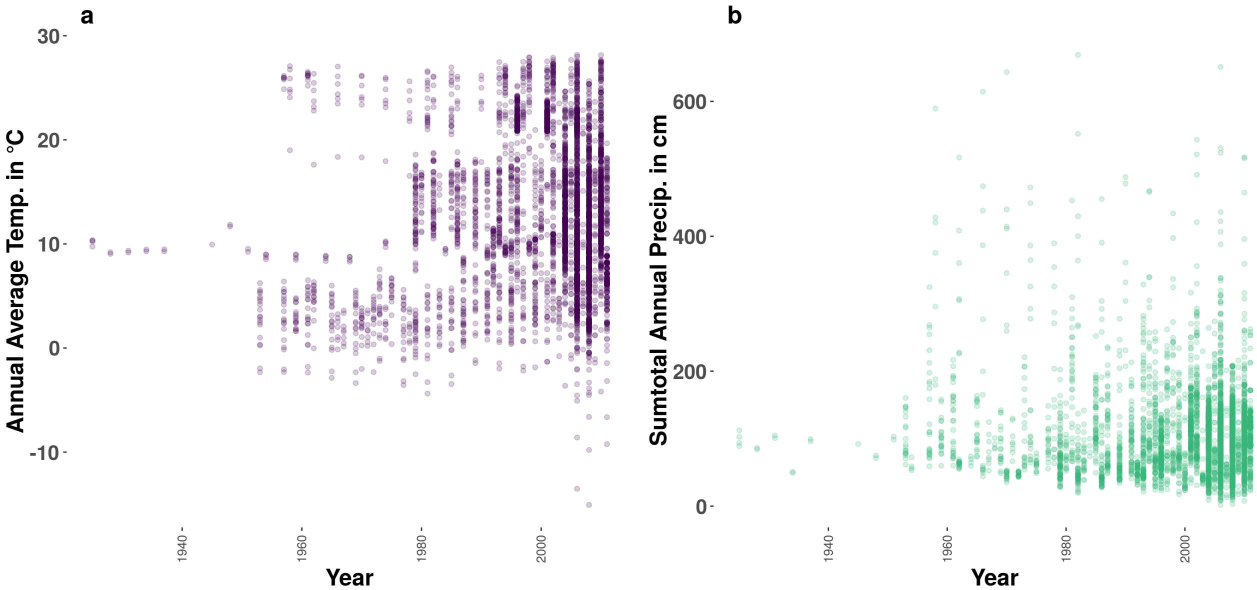

Figure S4: Plots of average temperature and sumtotal precipitation by year.

of the climate on social phenomena[3]. These data are on a 0.5x0.5 grid and are monthly from 1901 to 2013. I obtained the precipitation data from here and the temperature data from here. Using the *raster* package in **R** and employing the San Diego Supercomputer Center's Gordon supercomputer, I spatially averaged the grid cells to constituency boundaries for each historical month.

Annual Temperature

I calculate the year prior to election temperature variable as:

$$Temp._{jt} = \overline{12\ Months\ Prior\ to\ Election\ Temp._{jt}}$$

where j is constituency and t is election year. Temperature is measured in °C. Using yearly mean temperature is consistent with the literature on the effects of climate on aggregate economic output[4–6]. The distribution of these anomalies can be seen in Figure S3, panel (a) while temperature over time can be seen in Figure S4, panel (a).

Annual Precipitation

To calculate the annual sumtotal precipitation variable, I calculate the 12 months preceding an election's total precipitation:

$$Sumtotal\ Precip._{jt} = \Sigma 12\ Months\ Prior\ to\ Election\ Prcp._{jt}$$

where again j is constituency and t is election year.

Precipitation is measured in cm. The distribution of precipitation can be seen in Figure S3, panel (b) while annual precipitation over time can be seen in Figure S4, panel (b).

Climate Model Data

NASA NEX Bias-Corrected Spatially Downscaled Climate Forecast Data

For the forecast, I employ bias-corrected spatially downscaled (BCSD) climate forecast data from 21 global circulation model temperature and precipitation outputs in the CMIP5 model comparison project[7], using the RCP 8.5 emissions scenario[8]. These datasets consisted of daily level 0.25x0.25 grid cells for total precipitation and maximum and minimum temperatures (which were averaged to create the average temperature forecasts). The years span 2010-2099, though because of the size of these data, I select the years 2010, 2050, and 2099 for analysis. Again using the *raster* package in **R** and employing the San Diego Supercomputer Center's Gordon supercomputer, I spatially averaged the NEX BCSD grid cells to constituency boundaries. The NEX BCSD data can be obtained from here.

Regression Tables

Main Effect

In this section I present the regression table associated with the regression from Equation 1 in the main text. The unit of analysis is the constituency-year, with analysis weighted by the number of votes cast in each constituency-election. The dependent variable throughout is the change in the vote share of the party that won the highest number of votes in the last constituency election – the constituency incumbent party[1]. The main independent variable is annual average temperature in the twelve months prior to the election. The main model results are presented in model (1) of Tables S2.

Model (2) includes a squared precipitation term to check for a non-linear relationship, Model (3) includes controls for the month prior to election temperature and precipitation, Model (4) includes squared month prior meteorological variables to check for non-linear relationships, and Model (5) excludes all these controls, including only temperature. As can be seen, the results on the annual temperature bins remain consistent with the removal/inclusion of these controls. Because of the potential for precipitation to serve as an omitted variable – biasing coefficient estimates – I report the estimates of model (1) in the main text.

Time and Location Controls

The main specification employs constituency, year, election month, and country-specific year indicators to partial out the potentially confounding effects of location, time, and country-specific trends on the estimated annual temperature coefficients[6]. However, the results are robust to altering these specifications[9]. Table S3 presents the results of alternative specifications (with model (6) replicating the model from Equation 1 in the main text). The results are consistent across controlling for only constituency fixed effects (model (2)), controlling for only constituency and year fixed effects without election month or flexible country trends (model (3)), the exlusion of country-specific trends (model (4)), the replacement of country-specific year trends with continent-specific year trends (model (5)), and to controlling for all constituency, year, election month, and country-specific potentially unobserved, constant confounds (model (6)), same as main text Equation 1). Because the latter specification is most conservative, I select it as the main model as given by Equation 1 in the main text.

Bonferroni Correction

In this section I present the regression table associated with the regression from Equation 1 in the main text, calculating Bonferroni corrections for the p-values on the eight meteorological coefficients in the model. This is a conservative procedure for dealing with the potentially inflated family-wise error rate associated with multiple hypothesis testing for each coefficient on each bin in this non-linear specification[10,11]. Nonetheless,

Table S2: Annual Temperature, Precipitation, and Change in Incumbent Vote Share

	DV: Change in Incumbent Party Vote Share				
	(1)	(2)	(3)	(4)	(5)
$AnnualT \in (-\infty, -4]$	9.212	9.334	8.572	8.610	9.100
	(7.352)	(7.274)	(7.139)	(7.761)	(7.314)
$AnnualT \in (-4, 1]$	2.686	2.747	2.446	2.207	2.601
	(4.013)	(3.999)	(4.085)	(4.310)	(4.012)
$AnnualT \in (1, 6]$	2.164	2.262	1.992	1.691	2.108
	(3.304)	(3.276)	(3.467)	(3.584)	(3.303)
$AnnualT \in (6, 11]$	−0.179	−0.072	−0.367	−0.561	−0.224
	(1.915)	(1.867)	(1.987)	(2.072)	(1.917)
$AnnualT \in (11, 16]$	−1.783	−1.712	−1.863	−1.888	−1.803
	(1.538)	(1.543)	(1.671)	(1.724)	(1.528)
$AnnualT \in (21, 26]$	−9.024***	−8.993***	−8.906***	−8.858***	−8.897***
	(2.999)	(2.978)	(2.985)	(2.991)	(3.005)
$AnnualT \in (26, \infty]$	−16.100***	−16.558***	−16.105***	−15.943***	−15.803***
	(4.569)	(4.760)	(4.669)	(4.756)	(4.465)
Annual Precip.	−0.008	−0.038	−0.015	−0.015	
	(0.014)	(0.033)	(0.015)	(0.016)	
Annual Precip.^{2}		0.0001			
		(0.0001)			
Month Temp.			−0.531	−0.240	
			(0.488)	(0.386)	
Month Precip.				−0.012	
				(0.013)	
Month Temp.^{2}			0.072	0.073	
			(0.075)	(0.108)	
Month Precip.^{2}				−0.0001	
				(0.001)	
Constituency FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Election Month FE	Yes	Yes	Yes	Yes	Yes
Country:Year FE	Yes	Yes	Yes	Yes	Yes
Observations	4,880	4,880	4,880	4,880	4,880
R^2	0.453	0.453	0.454	0.454	0.453
Adjusted R^2	0.215	0.215	0.216	0.216	0.215
Residual Std. Error	6,106.697	6,105.695	6,102.489	6,102.820	6,106.203

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are in parentheses and are clustered on constituency and year

Table S3: Alternative Time and Location Fixed Effects

	DV: Change in Incumbent Party Vote Share					
	(1)	(2)	(3)	(4)	(5)	(6)
$AnnualT \in (-\infty, -4]$	2.335	12.445**	8.279	8.052	11.346	9.212
		(5.829)	(7.751)	(7.450)	(7.132)	(7.352)
$AnnualT \in (-4, 1]$	2.903**	10.709**	3.106	3.046	4.845	2.686
	(1.365)	(5.452)	(5.266)	(4.751)	(3.870)	(4.013)
$AnnualT \in (1, 6]$	1.036	7.929*	3.006	3.140	3.482	2.164
	(1.124)	(4.083)	(4.124)	(3.732)	(3.336)	(3.304)
$AnnualT \in (6, 11]$	−0.593	3.085	1.294	0.946	0.471	−0.179
	(1.435)	(3.704)	(3.116)	(2.581)	(2.333)	(1.915)
$AnnualT \in (11, 16]$	−1.630	−0.735	−0.581	−0.843	−1.148	−1.783
	(1.021)	(2.172)	(2.646)	(2.215)	(1.924)	(1.538)
$AnnualT \in (21, 26]$	−0.583	−10.405***	−9.464***	−9.336***	−8.560***	−9.024***
	(1.178)	(2.988)	(2.931)	(3.022)	(2.967)	(2.999)
$AnnualT \in (26, \infty]$	−3.397***	−15.212***	−14.782***	−14.500***	−15.281***	−16.100***
	(1.265)	(4.562)	(4.575)	(4.879)	(4.769)	(4.569)
Annual Precip.	−0.005	0.001	−0.007	0.003	0.002	−0.008
	(0.008)	(0.013)	(0.011)	(0.011)	(0.014)	(0.014)
Constant	−3.710***					
	(1.153)					
Constituency FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Election Month FE	No	No	No	Yes	Yes	Yes
Continent:Year FE	No	No	No	No	Yes	No
Country:Year FE	No	No	No	No	No	Yes
Observations	4,880	4,880	4,880	4,880	4,880	4,880
R^2	0.007	0.315	0.410	0.424	0.444	0.453
Adjusted R^2	0.005	0.076	0.191	0.207	0.212	0.215
Residual Std. Error	6,874.297	6,625.284	6,199.136	6,136.871	6,118.891	6,106.697

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors are in parentheses and are clustered on constituency and year after Bonferroni correction, temperatures above the $AnnualT \in (16, 21]$ bin still retain significance at p$<$0.05. Tables S4 presents this regression. Of note, the p-value on the $AnnualT \in (21, 26]$ coefficient after Bonferroni correction is 0.021 and is 0.003 for the $AnnualT \in (26, \infty]$ coefficient.

Table S4: Bonferroni Corrected p-Values for Main Specification

	DV: Change in Incumbent Party Vote Share
$AnnualT \in (-\infty, -4]$	9.212
	(7.352)
$AnnualT \in (-4, 1]$	2.686
	(4.013)
$AnnualT \in (1, 6]$	2.164
	(3.304)
$AnnualT \in (6, 11]$	−0.179
	(1.915)
$AnnualT \in (11, 16]$	−1.783
	(1.538)
$AnnualT \in (21, 26]$	−9.024**
	(2.999)
$AnnualT \in (26, \infty]$	−16.100***
	(4.569)
Annual Precip.	−0.008
	(0.014)
Constituency FE	Yes
Year FE	Yes
Election Month FE	Yes
Country:Year FE	Yes
Observations	4,880
R^2	0.453
Adjusted R^2	0.215
Residual Std. Error	6,106.697
Note:	*p<0.1; **p<0.05; ***p<0.01
	Standard errors are in parentheses and are clustered on constituency and year

Linear and Polynomial Specifications

The main specification employs temperature bins to flexibly estimate the non-linear relationship between temperature and changes in incumbent party vote share. Table S5 presents the results of alternative specifications of temperature, with temperature entering linearly (model (1)) and then entering with progressively higher order polynomials (models (2-4)). Fourth order polynomials (model (4)) gain marginal significance, as their functional form most closely approximates the functional form of Figure 1, panel (a) in the main text. However, because of the imposition of parametric functional form and the relative complexity of interpreting the marginal effects and standard errors associated with fourth order polynomials, I prefer the flexible non-linear estimation provided by Equation 1 in the main text[3,12].

Spatial and Serial Correlation

In the main text results, I report standard errors that allow for within-constituency and within-year correlations in the error term[13–15]. The use of standard errors clustered in this manner is common in the existing literature that examines the potential for climate change to alter social outcomes[6,16,17]. However, temperature and, to a lesser extent, precipitation are often spatially correlated. Thus, it is important to check to see if the inferential results are substantially affected by accounting for possible temporal and spatial correlation of the errors[3].

To flexibly account for both spatial dependence and serial dependence within constituencies, I implement nonparametric estimation of the variance-covariance matrices, producing heteroskedasticity, serial correlation,

Table S5: Linear and Polynomial Specifications

	DV: Change in Incumbent Party Vote Share			
	(1)	(2)	(3)	(4)
Annual Temp.	−1.072	0.385	−3.840	−2.364
	(0.852)	(2.862)	(2.624)	(1.804)
Annual Precip.	−0.007	−0.010	−0.014*	−0.017**
	(0.007)	(0.006)	(0.008)	(0.008)
Annual Temp.^{2}		−0.056	0.314	−0.161
		(0.109)	(0.215)	(0.169)
Annual Temp.^{3}			−0.009	0.025*
			(0.007)	(0.015)
Annual Temp.^{4}				−0.001*
				(0.0004)
Constituency FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Election Month FE	Yes	Yes	Yes	Yes
Country:Year FE	Yes	Yes	Yes	Yes
Observations	4,880	4,880	4,880	4,880
R^2	0.450	0.450	0.451	0.452
Adjusted R^2	0.211	0.212	0.213	0.214
Residual Std. Error	6,120.332	6,120.031	6,115.173	6,109.540

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are in parentheses and are clustered on constituency and year

Table S6: Conley Spatial Standard Errors

	DV: Change in Incumbent Party Vote Share	
	Multiway SE	Conley SE
	(1)	(2)
$AnnualT \in (-\infty, -4]$	8.279	8.279
	(7.751)	(6.444)
$AnnualT \in (-4, 1]$	3.106	3.106
	(5.266)	(4.302)
$AnnualT \in (1, 6]$	3.006	3.006
	(4.124)	(3.234)
$AnnualT \in (6, 11]$	1.294	1.294
	(3.116)	(2.982)
$AnnualT \in (11, 16]$	−0.581	−0.581
	(2.646)	(1.923)
$AnnualT \in (21, 26]$	−9.464***	−9.464***
	(2.931)	(3.067)
$AnnualT \in (26, \infty]$	−14.782***	−14.782***
	(4.575)	(4.686)
Annual Precip.	−0.007	−0.007
	(0.011)	(0.018)
Constituency FE	Yes	Yes
Year FE	Yes	Yes
Observations	4,880	4,880
R^2	0.410	0.410
Adjusted R^2	0.191	0.191
Residual Std. Error	6,199.136	6,199.136

Note: *p<0.1; **p<0.05; ***p<0.01
Spatial HAC Conley standard errors use 1,000km bandwidth.
Standard errors in model (1) are clustered on constituency and year.

and spatial correlation robust (Conley) standard errors[18–20].[1] This method allows for contemporaneous spatial correlations between constituencies whose centroids fall within a wide limiting proximity (1,000 kilometers) to one another. Of note, the Conley code allows for only two sets of fixed effects, so in the examinations of spatial dependence I include constituency and year fixed effects only, excluding election month and country-specific year fixed effects.

The results of calculating the standard errors for the main text regression in this manner – using a 1,000km constituency centroid-to-centroid cutoff and allowing for full serial correlation – are presented in Table S6. As can be seen, the Conley standard errors are only slightly larger than the standard errors clustered on constituency and year, and resultant p-values are still highly significant on temperature bins greater than 21°C. Of important note, the median distance from a constituency's centroid to the nearest centroid of its neighboring constituency is 55 kilometers. Over 99% of constituencies' centroids fall within 1,000km of the centroid of their nearest neighbor.

Rich and Poor

In this section I present the regression tables associated with the regression from the main text that splits Equation 1 by rich versus poor countries (countries above or below the global average per-capita income in 1980, similar to how Burke et. al (2015) conduct their split using median income in 1980[6]). 'Rich' countries in this split are: Canada, Finland, Germany, Iceland, Austria, Luxembourg, Norway, Portugal, Spain, Switzerland, and the United States. 'Poor' countries in this split are: Colombia, Costa Rica, Argentina, Guyana, Honduras, Romania, Brazil, and Zambia. As can be seen, the sample of elections from rich countries is over four times as large as that from poor countries. Table S7 presents the results of these regressions. Though the sample size is smaller for poor countries, the effects of hot temperatures across constituencies in these nations still gain significance at standard levels. The coefficients on the temperature bin above 21°C in rich countries is negative but gains significance only at the $p < 0.10$ level.

Agricultural and Non-Agricultural

In this section I present the regression tables associated with the regression from the main text that splits Equation 1 by agricultural versus non-agricultural constituencies (constituencies above or below the median of percentage of average remote-sensed croplands[21]). Table S8 displays the number of unique constituencies that are classified as either agricultural or non-agricultural for each country in the sample, excluding Zambia. Remote sensing technologies perform poorly at acurately classifying agricultural lands in Sub-Saharan Africa[22], and thus I omit Zambia from the main agricultural analysis.

Table S8: Number of Ag. and Non-Ag. Constituencies by Country

Country	Ag. Constituencies	Non-Ag. Constituencies
Argentina	6	18
Austria	22	21
Brazil	8	19
Canada	147	161
Colombia	15	18
Costa Rica	6	1
Finland	1	14
Germany	15	1
Guyana	2	8
Honduras	13	5
Portugal	14	6

[1]I thank Darin Christensen and Thiemo Fetzer for providing the basic **R** code – in turn derived from Solomon Hsiang's code[20] – that I modified to calculate Conley errors.

Country	Ag. Constituencies	Non-Ag. Constituencies
Spain	44	8
Switzerland	18	8
United States	213	222

Table S9 presents the results of regressions that split the sample by agricultural versus non-agricultural constituencies. Of note, as can be seen in models (3) and (4) that include Zambia, the results are not particularly sensitive to the inclusion or exclusion of Zambian elections, even though agriculture is measured with high-error in the country. Because of the relatively low level of agricultural intensification in Zambia[21], all of its constituencies are classified as non-agricultural (due to mismeasurement mentioned above). Hot temperatures in agricultural constituencies produce significantly more negative changes in incumbent party vote share. Hot temperatures in non-agricultural constituencies are also associated with reduced vote share, though these effects do not gain significance.

Income and Agriculture

In this section I present the tables associated with the regression from the main text that splits Equation 1 by non-agricultural constituencies from rich countries versus agricultural constituencies from poor countries. I also investigate the differential effects between rich country agricultural constituencies and poor country non-agricultural constituencies. Table S10 displays the number of unique constituencies that are classified as either poor agricultural, rich agricultural, poor non-agricultural, or rich non-agricultural for each country in the sample.

Table S10: Ag./Non-Ag. Constituencies by Rich and Poor Countries

Country	Rich Ag.	Poor Ag.	Rich Non-Ag.	Poor Non-Ag.
Austria	22	0	0	0
Canada	147	0	0	0
Finland	1	0	0	0
Germany	15	0	0	0
Luxembourg	4	0	0	0
Portugal	14	0	0	0
Spain	44	0	0	0
Switzerland	18	0	0	0
United States	213	0	0	0
Argentina	0	6	0	0
Brazil	0	8	0	0
Colombia	0	15	0	0
Costa Rica	0	6	0	0
Guyana	0	2	0	0
Honduras	0	13	0	0
Romania	0	41	0	0
Austria	0	0	21	0
Canada	0	0	161	0
Finland	0	0	14	0
Germany	0	0	1	0
Iceland	0	0	8	0
Norway	0	0	19	0
Portugal	0	0	6	0
Spain	0	0	8	0
Switzerland	0	0	8	0

Country	Rich Ag.	Poor Ag.	Rich Non-Ag.	Poor Non-Ag.
United States	0	0	222	0
Argentina	0	0	0	18
Brazil	0	0	0	19
Colombia	0	0	0	18
Costa Rica	0	0	0	1
Guyana	0	0	0	8
Honduras	0	0	0	5
Zambia	0	0	0	150

Table S11 presents the results of regressions that split the sample by rich country agricultural constituencies versus poor country agricultural constituencies (models (1-2)) as well as by rich vs. poor country non-agricultural constituencies (models (3-4)). Because of above mentioned issues with measurement of croplands in Zambia, I exclude it from these analyses. As can be seen, agricultural constituencies in poor nations exhibit the largest significant negative response to high temperature shocks. Of note, high temperatures in non-agricultural constituencies in rich nations also produce negative changes in incumbent vote share, though this effect is only significant at the $p < 0.10$ level.

Alternative Temperature Bins

In this section I vary the size of the temperature bins associated with model (1) of Tables S2, the main specification, ensuring the reference category still contains 18.5°C (65°F). Bin sizes of 2°C and 1°C each demonstrate reductions in vote with increasing annual temperatures. Splitting the bin sizes smaller than 5°C reduces the number of observations within each bin and increases associated standard errors. Because each 5°C bin includes more constituencies in each bin from a variety of countries, I choose 5°C bin sizes for the main specification. These results can be seen in Figure S5

Frequency of Close Elections

To evaluate the size of the effect of estimated electoral swings, I use the full Constituency Level Electoral Archive (CLEA) for each country in the main dataset, which provides a broader accounting of historical elections than does the sample that is constrained by the availability of spatial electoral boundaries. The CLEA dataset has 59,171 total constituency-election observations for the countries included in this analysis.

To see whether the magnitude of the marginal effect of temperature increases on vote share has the potential to be politically meaningful, I examine the number of constituency-level elections with historical temperatures between 16°C and 21°C whose returns were closer than the nine percentage point reduction in the change in incumbent vote share associated with a shift between this baseline category of 16°C-21°C to the 21°C-26°C range. Of important note, an incumbent's loss of vote share means – mechanically – that challenging parties will receive a boost of some fraction of the lost vote share in that constituency. In the case of constituencies with only two main parties competing for power, a nine percentage point reduction in incumbent vote share produces an eighteen percentage point swing in vote share. In the full historical electoral data 19% of all constituencies have only two parties while 39% have either only two or only three parties.

Of constituency-level elections in constituencies with annual temperatures between 16°C and 21°C, 31% had parties that won by nine percentage points or less, the marginal effect of moving from the 16°C-21°C baseline bin to the 21°C-26°C bin, or the effect of a 5°C average increase in annual temperature – approximately the average increase projected by 2099 by climate models for these constituencies as compared to the 2010 baseline (more precisely, 4.5°C under the RCP8.5 emissions scenario). In electoral contests with only two parties, the effect of a nine percentage point reduction in vote share is amplified into an eighteen percentage

Table S7: Regressions Splitting by Poor vs. Rich Countries

	DV: Change in Incumbent Party Vote Share	
	Poor Countries	Rich Countries
	(1)	(2)
$AnnualT \in (-\infty, -4]$		8.668
		(7.664)
$AnnualT \in (-4, 1]$		2.133
		(4.003)
$AnnualT \in (1, 6]$	−7.442	1.458
	(17.238)	(3.387)
$AnnualT \in (6, 11]$	25.776***	−2.061
	(8.767)	(1.684)
$AnnualT \in (11, 16]$	10.875	−2.468*
	(7.112)	(1.433)
$AnnualT \in (21, 26]$	−7.841*	−13.677*
	(4.058)	(7.912)
$AnnualT \in (26, \infty]$	−15.162***	
	(5.287)	
Annual Precip.	−0.018	0.010
	(0.015)	(0.026)
Constituency FE	Yes	Yes
Year FE	Yes	Yes
Election Month FE	Yes	Yes
Country:Year FE	Yes	Yes
Observations	947	3,933
R^2	0.676	0.345
Adjusted R^2	0.438	0.086
Residual Std. Error	6,627.654	6,021.438

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are in parentheses and are clustered on constituency and year

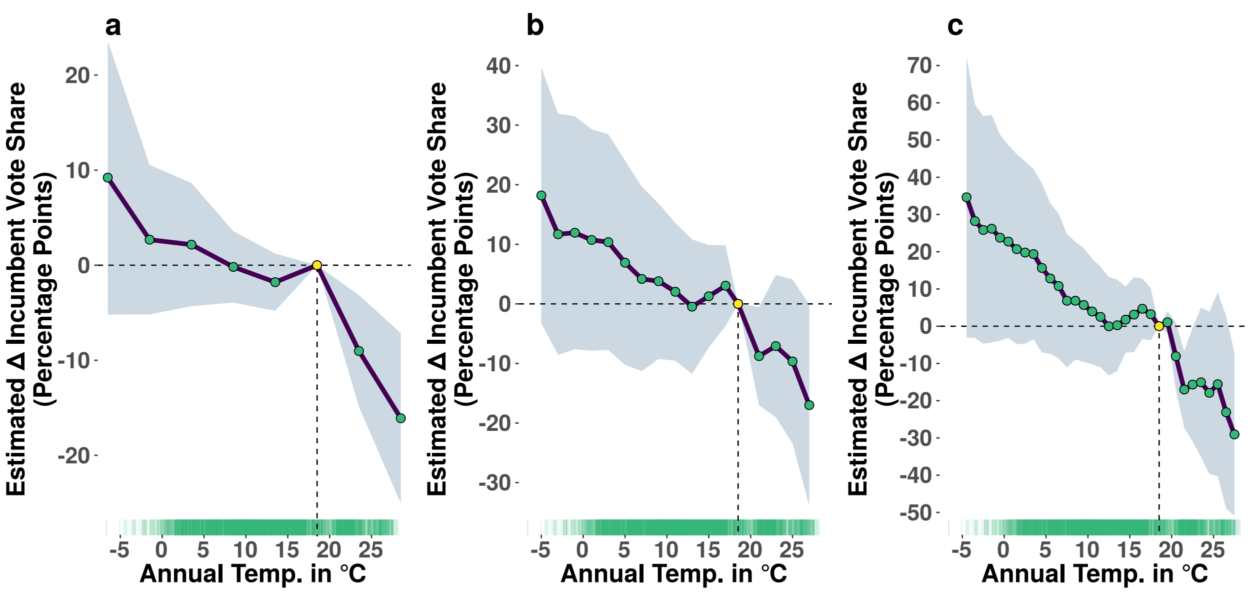

Figure S5: The purple line with green points in each panel plots the same relationship as seen in Figure 1, panel (b) in the main text (which is replicated in panel (a) of this figure). In panel (b) bin size is reduced to two degrees Celsius. In panel (c) bin size is reduced to one degree Celsius. As can be seen, there is close correspondence between the functional forms in each, with changes in incumbent party vote share becoming more negative with increases in temperature.

Table S9: Regressions Splitting by Non-Ag. vs. Ag. Constituencies

	DV: Change in Incumbent Party Vote Share			
	Non-Ag.	Ag.	Non-Ag, Zambia	Ag., Zambia
	(1)	(2)	(3)	(4)
$AnnualT \in (-\infty, -4]$	15.288		15.305	
	(11.053)		(11.208)	
$AnnualT \in (-4, 1]$	7.366	28.221**	7.384	28.221**
	(7.192)	(14.173)	(7.295)	(14.173)
$AnnualT \in (1, 6]$	7.477	1.029	7.493	1.029
	(6.794)	(7.728)	(6.892)	(7.728)
$AnnualT \in (6, 11]$	4.540	−1.685	4.552	−1.685
	(5.769)	(2.107)	(5.850)	(2.107)
$AnnualT \in (11, 16]$	1.795	−2.680	1.795	−2.680
	(2.486)	(1.854)	(2.519)	(1.854)
$AnnualT \in (21, 26]$	−9.947	−9.706***	−9.412	−9.706***
	(8.494)	(3.546)	(8.439)	(3.546)
$AnnualT \in (26, \infty]$	−18.175	−14.847***	−17.646	−14.847***
	(11.982)	(5.746)	(12.081)	(5.746)
Annual Precip.	−0.028	0.007	−0.029	0.007
	(0.038)	(0.020)	(0.038)	(0.020)
Constituency FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Election Month FE	Yes	Yes	Yes	Yes
Country:Year FE	Yes	Yes	Yes	Yes
Observations	2,281	2,271	2,609	2,271
R^2	0.387	0.512	0.401	0.512
Adjusted R^2	0.103	0.270	0.099	0.270
Residual Std. Error	5,843.705	6,754.601	5,572.362	6,754.601

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are in parentheses and are clustered on constituency and year

point electoral swing. In the historical data, 41% of two-party constituencies in this temperature range were won by 18 percentage points or less. Ultimately, the sizable effects associated with increases in annual temperature projected by 2099 have the potential to alter the outcomes of a large portion of future electoral contests.

Forecast Details

Main Forecast Model

The primary specification from Equation 1 in the main text uses annual temperature bins to non-linearly estimate the relationship between temperature and changes to constituency-level incumbent party vote share (the results of estimating this equation can be seen in Tables S2). One option to conduct a forecast with future climate model data would be to directly employ the estimated coefficients from model (6) of Table S2 in the forecast. Doing so would have the conservative effect of assigning future temperature values that fall outside of the support of the historical distribution to the maximum bin in the historical data. However, employing this method would also have a number of drawbacks. First, the underlying historical temperature distribution is not perfectly smooth, given the cross-country variations in temperature regimes. Because bin-width in Equation 1 is 5°, constituencies whose average temperature was just greater than 21°C (70°F) would be assigned the coefficient associated with the 21-26°C bin until future temperatures increased beyond 26°C. Thus, many constituencies might show zero effect of future climatic changes simply because their full predicted warming this century might not push them into the next higher temperature bin. The second drawback to this approach relates to the conservativeness associated with assigning future values of temperature to the maximum historical temperature coefficient. One may reasonably expect that the effects of temperature on human economic, psychological, and physiological well-being will not remain flat as

Table S11: Regressions Splitting by Rich/Poor, Ag./Non.Ag

	DV: Change in Incumbent Party Vote Share			
	Rich Ag.	Poor Ag.	Rich Non-Ag.	Poor Non-Ag.
	(1)	(2)	(3)	(4)
$AnnualT \in (-\infty, -4]$			14.967	
			(11.883)	
$AnnualT \in (-4, 1]$	31.583**		7.016	
	(13.710)		(7.854)	
$AnnualT \in (1, 6]$	4.100	−8.436	7.155	
	(7.232)	(20.040)	(7.418)	
$AnnualT \in (6, 11]$	−3.289**	22.985***	4.255	7.172
	(1.441)	(7.171)	(6.366)	(8.583)
$AnnualT \in (11, 16]$	−2.991*	2.517	1.561	5.358
	(1.785)	(4.983)	(2.612)	(4.573)
$AnnualT \in (21, 26]$	0.435	−11.760***	−20.604*	4.428
	(8.963)	(3.453)	(10.654)	(6.676)
$AnnualT \in (26, \infty]$		−17.645***		−3.936
		(6.236)		(12.618)
Annual Precip.	0.030	−0.012	−0.023	−0.044
	(0.038)	(0.020)	(0.028)	(0.136)
Constituency FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Election Month FE	Yes	Yes	Yes	Yes
Country:Year FE	Yes	Yes	Yes	Yes
Observations	1,927	344	2,006	268
R^2	0.335	0.816	0.393	0.374
Adjusted R^2	0.031	0.620	0.129	−0.392
Residual Std. Error	6,686.736	7,537.541	5,393.705	10,101.550

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are in parentheses and are clustered on constituency and year

future temperatures exceed historical maximums. Thus using only binned coefficient values may be an overly conservative approach.

To address these issues, I build a linear spline function that matches the functional form revealed by connecting the midpoints of the historical temperature bins to one another. This has the advantage of allowing constituencies to increase or decrease linearly between the midpoints from Equation 1. It also has the added benefit of allowing for linear extrapolation of historical relationships to novel future temperatures, and is thus likely to more accurately reflect human exposure to heightened temperatures. I fit the coefficient on year prior sumtotal precipitation to future predicted precipitation data and include it in the fitted values of the forecast. The spline function used is depicted by the red line in Figure S6.

Alternative Forecast Model

In this section I depict the results of employing the estimated coefficients from Equation 1 directly – coupled with climate model predictions – to conduct the forecast. As can be seen in the replication of Figure 5 from the main text, in Figure S7, the average constituency prediction is for a decrease of -1.71 percentage points in incumbent party vote share. Because some constituencies do not completely shift from one temperature bin to another, their change from 2010 to 2050 to 2099 is largely determined by changes in annual precipitation, given by the negative linear slope on annual precipitation from Equation 1. Even with this forecasting procedure, the average climate change induced reduction is negative as constituencies are pushed into higher temperature regimes.

I replicate Figure 6 from the main text in Figure S8. The set of countries likely to see the greatest reductions remains the same, though the error bars increase as a result of increased intra-country variance due to the coarser bin function of Equation 1 as compared to the spline forecast.

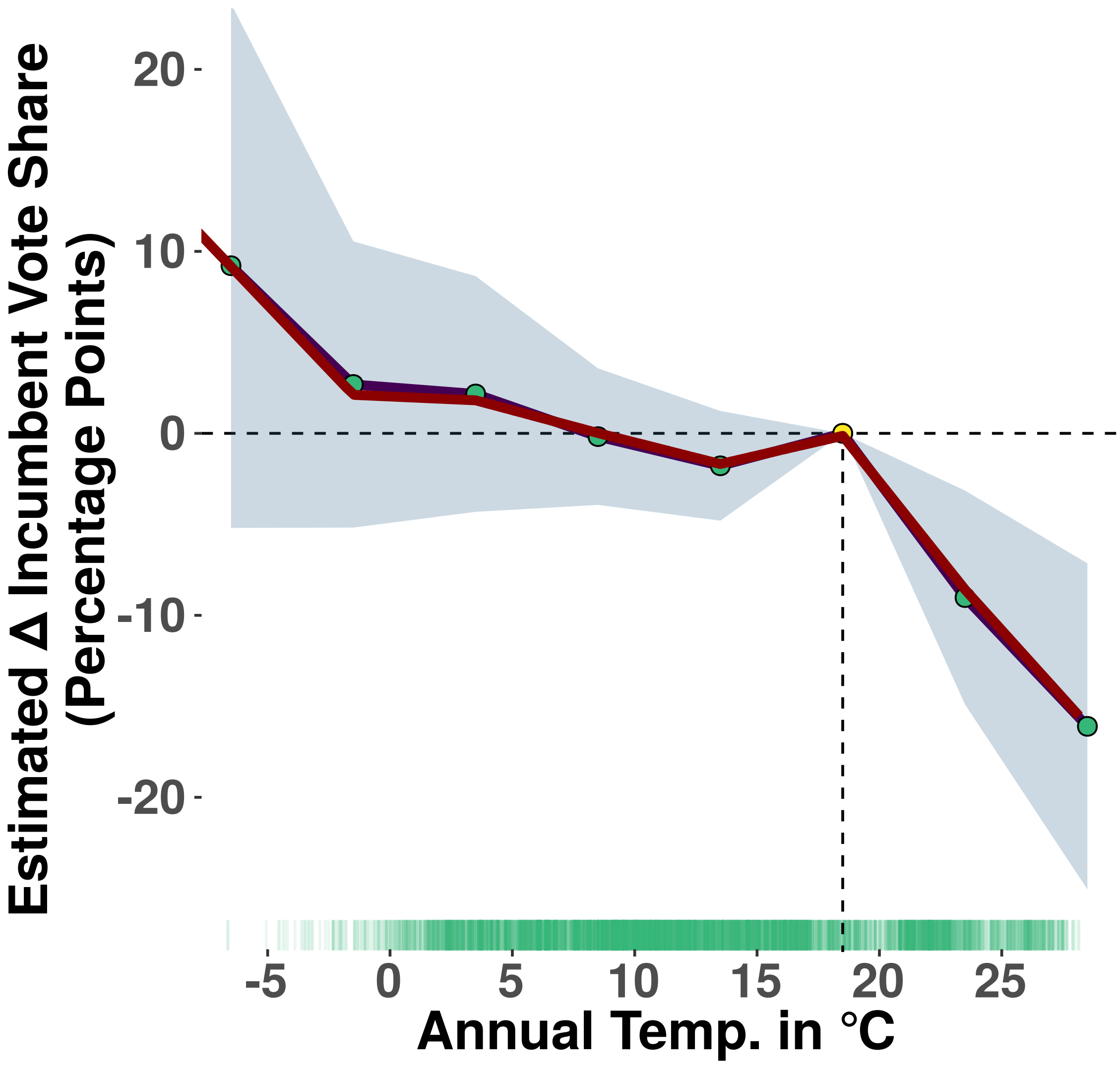

Figure S6: The purple line with green points plots the same relationship as seen in Figure 1, panel (b) in the main text. The red line depicts the functional form produced by the defined linear spline. As can be seen, there is close correspondence between the slopes between the linear spline function and the midpoints of the temperature bins from Equation 1.

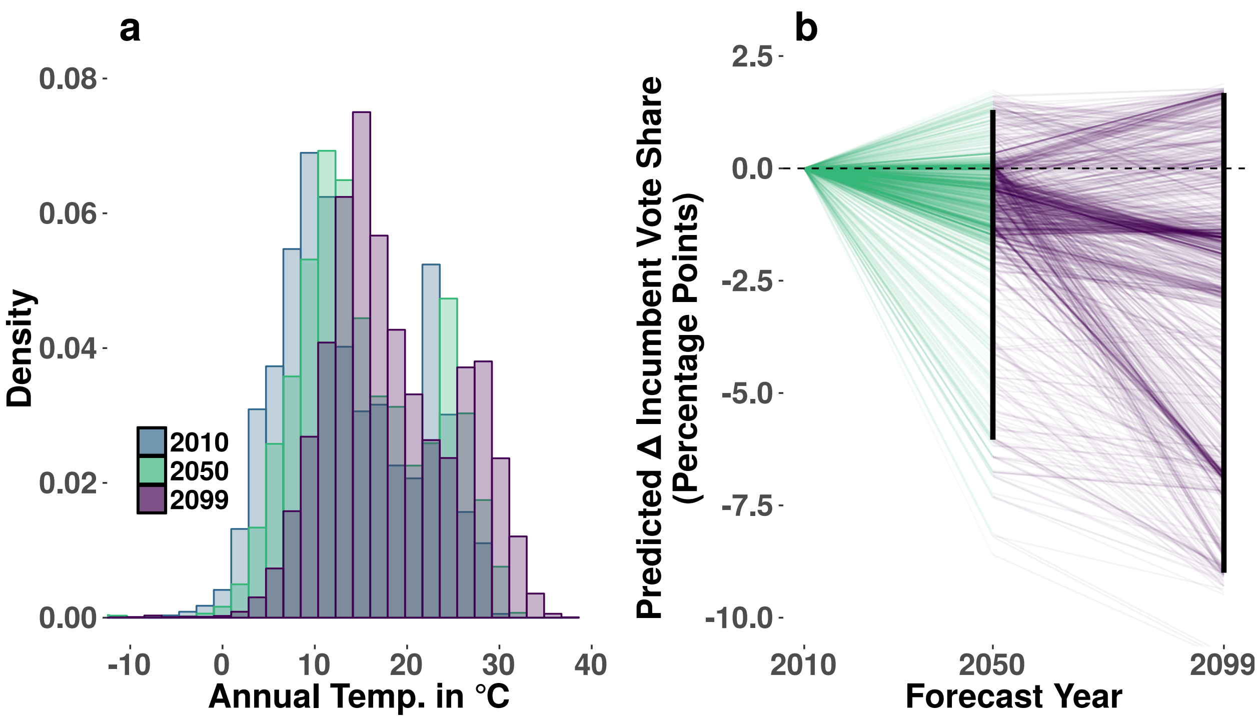

Figure S7: This figure reproduces Figure 5 from the main text, employing the estimated coefficients from Equation 1 directly to conduct the future forecast. As can be seen, because many constituencies do not completely shift from one temperature bin to another, their change from 2010 to 2050 to 2099 is largely determined by changes in annual precipitation, given by the negative linear slope on annual precipitation from Equation 1. However, as can be seen, even with this forecasting procedure, the median constituency is expected to see a notable reduction in incumbent party vote share due to future climate change as constituencies are pushed into different temperature regimes on average.

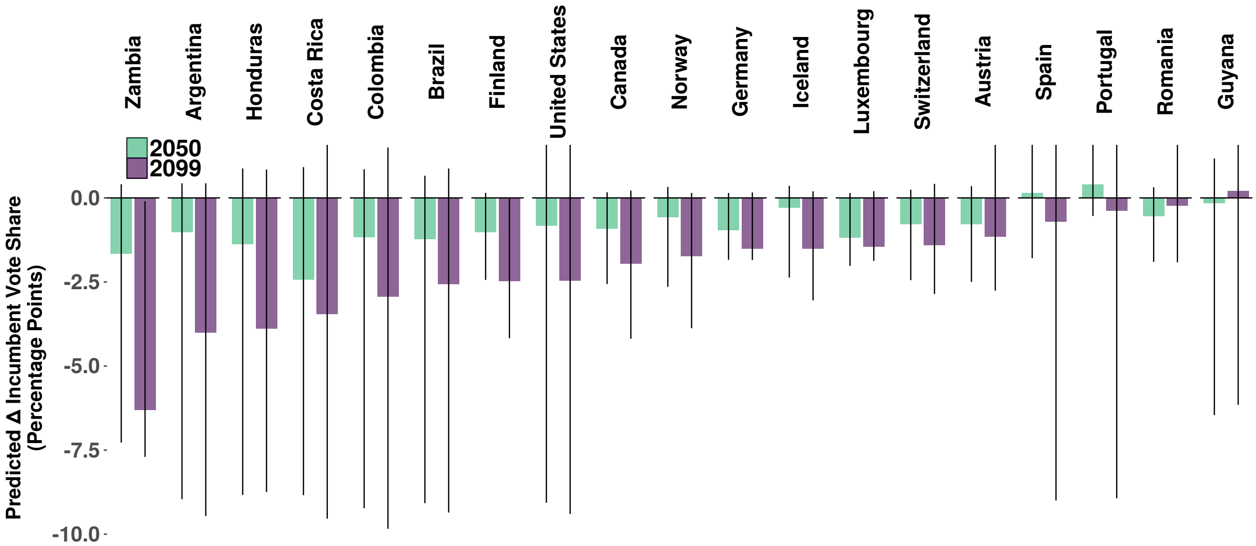

Figure S8: This figure reproduces Figure 6 from the main text, employing the estimated coefficients from Equation 1 directly to conduct the future forecast. Because many constituencies do not completely shift from one temperature bin to another, their change from 2010 to 2050 to 2099 is largely determined by changes in annual precipitation, given by the negative linear slope on annual precipitation from Equation 1. This results in a high intra-country range in predicted constituency changes to incumbent vote share, as represented by the error bars in this figure. However, as can be seen, even with this forecasting procedure, the countries predicted to be most affected by future warming, as well as the magnitude of these average predictions at the country level, remain similar.

Constituency-Level Forecast

To conduct the forecast plotted in Figure 5 in the main text, I first calculate the 2010, 2050, and 2099 average maximum temperature, minimum temperature, and precipitation forecasts from all 21 of NASA's NEX GDDP bias corrected statistically downscaled (BCSD) climate models[23] (drawn from the CMIP5 model ensemble[7] using the RCP8.5 'business-as-usual' model scenario[8]). This gives me a yearly average value for each grid cell across the globe. Since the NEX data do not provide average temperatures directy, I take the average between maximum and minimum temperatures as the yearly average temperature. Next, I extract – using spatial weighting – both the annual temperature and sumtotal annual precipitation forecasts to the constituency boundaries in the historical data for each of 2010, 2050, and 2099. These forecasts then represent the constituency-levl annual climate model projections across all 21 climate models in the NEX data.

I then employ the fitted spline model from *SI: Main Forecast Model* to calculate the fitted values associated with the historical model for each future year for each of the 21 BCSD climate models. Then, for each constituency-year and model, I subtract the fitted values in 2050 from the baseline period of 2010 and then take the marginal difference from 2050 to 2099. This procedure results in an estimated change in incumbent party vote share due to climate change for each constituency-year, for each climate model. I then take the average for each constituency across the 21 models and present these values in panel (b) in the main text Figure 5.

Country-Level Forecast

To calculate forecasts at the country level for 2050 and 2099, I again employ the spline fit from *SI: Main Forecast Model* to calculate the difference in fitted values for each constituency, for each climate model. In this forecast, I calculate the difference between 2050 and 2010 and between 2099 and 2010, respectively. I then, for each country in the data, take the average predicted change across all of a country's constituencies in a given future year and use this as the country-level prediction in Figure 6 in the main text.

The black error bars in this plot represents the 2.5th to 97.5th percentile range of constituency-level predictions across all climate models within a country. Countries that have larger error bars have greater climatic heterogeneity within in them and/or increased climate model uncertainty regarding changes to their future temperature and precipitation distributions.

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