26th International Congress on Modelling and Simulation, Adelaide, SA, Australia, 30 Nov–4 Dec 2025
mssanz.org.au/modsim2025

How Climate Change Affects Protest Behaviour

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Abstract: In this paper, we develop a theoretical framework for the pathways through which climate change can influence protest occurrence, frequency, and intensity. Our approach sits at the intersection of quantitative political geography and applied econometrics. We draw from economics and social science literature that investigates the ways in which climate change causes direct and indirect, economic and non-economic harms. We combine these findings with examinations of the determinants of protest behaviours in the politics literature.

We construct a novel panel dataset of climate change, protest, and socioeconomic and demographic variables from three data sources: The Global Database of Events Language and Tone (GDELT), the NOAA Monthly U.S. Climate Gridded Dataset (NClimGrid), and the IPUMS National Historical Geographic Information System (NHGIS). The completed dataset contains 540 months of observations over 433 United States congressional districts from 1979 to 2023 (n=233,820). It includes over 300,000 protest events.

To examine the role of changing temperature and precipitation in driving protest outcomes, we employ hurdle models using logit estimators to first examine the probability of a protest occurring, and second truncated Poisson regressions to model the count and intensity of protest events conditional on at least one event occurring in a given month.

We find that temperatures rising above a districts historical long-run normal are associated with a decline in the probability of a protest occurrence, but an increase in the number of protest events conditional on at least one event occurring. Precipitation increase is not correlated with the probability of a protest occurring, but it is strongly connected with the increase in the number of protests conditional on one event. These relationships are strongest over the 5- to 10- year pre-event average climate deviations, indicating the importance of long-run, persistent climate changes. Uncertainty increases when measuring 20-year pre-event average climate, possibly indicating adaptive capacity of some districts but not others.

These relationships may, in part, be explained by the effect of climate change leading to resource constraints limiting time and financial resources, ultimately decreasing the likelihood of protests in a given month. However, if a protest occurs, it is more likely to be accompanied by an increasing number of protests if temperature and precipitation are higher than normal. Considering the trend for both in the US is an alarming increase, this suggests clusters of intense protest activity into the future.

While we caution over-reliance on our findings due to some plausible dataset limitations, the presence of localised spatial autocorrelation in some of the time periods, these findings are yet another indication for policymakers that climate change harm is affecting constituents. Where the size of grievances and other facilitating determinant factors overcome the barriers to participation, unmitigated climate change is likely to lead to more frequent protests.

Keywords: *Climate change, protest behaviour, panel data, United States, hurdle model*

1 INTRODUCTION

Climate change causes significant economic and non-economic harm (Dell et al., 2014; Tschakert et al., 2019), however empirical examinations of people's protest responses to such harm are limited. Much of the literature concerned with the connection between climate change and protest is focused on conflict-prone contexts, e.g. Hendrix and Salehyan (2012). This is problematic, first, because it may incorrectly suppose a response to climate factors as inherently violent, irrational, and implicitly confined to particularly vulnerable locales. Instead, protesters can be considered strategic actors participating in a dialogue that is critical to a healthy democracy (Chenoweth et al., 2022; McVeigh and Smith, 1999). Second, selecting conflict-prone regions amounts to sampling on the dependent variable Adams et al. (2018). Further literature examines the occurrence and determinants of climate change protests (Bechtoldt and Schermelleh-Engel, 2025; Fritz et al., 2023). We take a broader view of the role of climate change in influencing protest behaviours.

Climate change can exert direct physiological and psychological effects, and indirect welfare effects by exacerbating social, economic, and environmental factors (Miles-Novelo and Anderson, 2019; Hendrix et al., 2023). Those affected may or may not be aware of climate change's role, but it results in harm nonetheless. Following harm and observing some institutional response (or lack thereof), the affected may develop a grievance. A grievance is translated into action through eligibility and willingness to mobilise (availability) (Beyerlein and Hipp, 2006; Schussman and Soule, 2005).

Eligibility and participation depend on determinants that predict harm, feelings of grievance, and participation. We group these into biographical, structural, and socio-psychological categories (Cohen et al., 2001; Eisinger, 1973; Lehman-Wilzig and Ungar, 1985; McVeigh and Smith, 1999; Saunders and Hayes, 2024). Biographical availability refers to the absence of personal constraints (consider income, employment, education, gender, race, marital status, children, age). Structural factors involve networks that enable awareness and recruitment, alongside institutional and societal conditions such as freedom to protest, democratisation, regime type, urbanisation, globalisation, and population size. Socio-psychological factors relate to perceptions and social interaction (i.e., values, group identity, expectations of others, perceived legitimacy and efficacy, morality, and emotions).[1]

Following McVeigh and Smith (1999), ex-post grievance, people may act within institutions, such as voting against the deemed-inadequate incumbent, act outside institutions, such as protesting, or fail to act, which could be motivated by disaffection. Those unaffected by the climate-induced harm may also participate (which we term solidarity), acting on either empathy self-interested concern about perceived risk of future harm.

2 DATA AND METHODOLOGY

To empirically test some of the plausible pathways for climate change to affect protest behaviour, we employ the Global Database of Events, Language, and Tone (GDELT) Events Database Version 1.0 (Leetaru and Schrodt, 2013). We combine this with temperature and rainfall data from the National Oceanic and Atmospheric Administration's (NOAA) Monthly U.S. Climate Gridded Dataset (NClimGrid) (Vose et al., 2014), which we spatially aggregate to the district level. We also link these to census-based variables sourced from the National Historical Geographic Information System (NHGIS) (Manson et al., 2023), which we temporally interpolate and spatially aggregate from the census-tract level by developing area-based crosswalks.

GDELT is a massive online automated system that extracts event information from thousands of media sources to compile data about conflict and cooperation events occurring around the world. From this source, we have compiled events covering the contiguous United States from 1979-2023, containing 330,110 protest events.

Our primary dependent variable is the number of protests in a district-month. We also employ several proxy measures of protest intensity, including the number of mentions across articles, unique articles, and news sources that report on the event. Two further intensity measures include a Goldstein score, which ranks events by type in terms of their potential for disruption, and an average tone measure, which classifies the average tone of reporting on the event on a scale of strongly negative to strongly positive.[2]

We construct climate change explanatory variables as the rolling 20-year district area averages of temperature and rainfall, as a deviation from a 20-year historical normal temperature and rainfall averages by district (i.e. 1895-1914, being the first 20 years of available data). This approach follows the accepted measure of climate

[1] Our data do not cover most structural or socio-psychological factors, which we acknowledge as a limitation.
[2] Average Tone and Goldstein Score are transformed from their original into a proportion where 0 is the lowest and 1 is the highest intensity. Refer to Schrodt (2012) for original variables.

change in scientific literature as per Fyfe et al. (2021). Since we calculate baselines and deviations by month before aggregating, we also account for seasonality due to the monthly temporal resolution of our panel.

The variables included as controls throughout our study (as motivated by prior literature on determinants of protest) include: district population, population density, unemployment rate, poverty rate, share of renter-occupied housing units, mean commute duration, mean resident age, percentage of residents who are married, female, adult, Black, Indigenous, Asian/Islander, Hispanic, other races, foreign-born, and hold a bachelor's degree or higher.

The data forms a balanced panel of districts (433) over months (540) to create a total of 233,820 observations. Some variables are only present where at least one event is recorded (63,756 observations).

We employ a hurdle model to assess the role of climate change in producing changes to protest frequency and intensity (Cameron and Trivedi, 2022). The first stage is a binary logit model capturing extensive margins (protest occurrence), and the second stage is a truncated Poisson model capturing intensive margins (protest frequency and intensity conditional on occurrence of at least one event).[3] This is appropriate given the presence of a large number of non-event district-months. We incorporate district fixed effects to account for time-invariant differences between districts (e.g., baseline political engagement, institutional capacity, political leanings, geographic factors) and month-year fixed effects to control for time-varying factors. For example, time trends in recorded protests are likely to be linked to increased media coverage, and we do note a substantial rise in protest events in the dataset over time. Rather than traditional "dummy" fixed effects, which can be problematic in non-linear models (Neyman and Scott, 1948), we include Mundlak variables as controls following Wooldridge (2021), which act in the spirit of fixed effects. We also report district cluster-robust standard errors to account for serial correlation in the errors within districts over time, especially given the use of overlapping long-run climate variables.

3 RESULTS

We display preliminary results of a series of regressions in Table 1. Model (1) indicates that long-run temperature and precipitation rise do not share statistically significant relationships at aggregate with the likelihood of at least one protest occurring in a given district-month. This does not preclude the likelihood that harm and associated grievance exists; however, protests may be a less common response since participation is a high-effort activity, subject to free-riding and beliefs about the (in)efficacy of action (Boulianne et al., 2020).

Increased temperature and precipitation both display statistically significant positive effects on the number of protest events (conditional on at least one event occurring), per Model (2). It is perfectly reasonable for the sign of the coefficient on stage one to be negative, and stage two be positive, since determinants may limit the likelihood of protest despite the presence of a grievance, but in the event that these are overcome, the scale of climate-induced grievances may become more evident. Models (3) through (7) present different proxy measures for intensity, conditional on a protest event occurring. All indicate a negative, but not statistically significant, relationship between temperature or precipitation deviation and aggregate measures of intensity. We refrain from drawing any significant conclusions from these models, given some drawbacks of these variables in acting as proxies for intensity. For example, the average tone of an article is used a a proxy for the intensity of the protest, but could certainly be influenced by media coverage bias.

Importantly, despite compression from our fixed effects approach, the residuals retain meaningful dispersion in our temperature and precipitation deviation (±0.5°C and ±12mm), providing sufficient variation for identification. We conduct Likelihood-Ratio tests on both stages with and without controls, and with and without Mundlak variables, and they reconfirm our chosen inclusions as appropriate. Furthermore, while the appropriateness of certain control variables may be debated, given that climate change could act through them to influence protest behaviour, the inclusion (or exclusion) of these controls has a modest effect on the magnitude of the coefficients. It does not change the direction of the relationships but helps attenuate errors. We argue that each control may independently affect protest outcomes, making their inclusion important for estimation accuracy. We intend to explore their role as mechanisms in subsequent study.

3.1 Recency Effects

The importance of the path, size, and timing of shocks to protest outcomes has been the subject of multiple investigations (Correa et al., 2025; Davies, 1962). Temperature or precipitation shocks that happened more recently, or average changes over shorter time windows, may be more easily perceived, more difficult to adapt

[3] We also use conditional fractional logit models on Goldstein Score and Average Tone outcomes.

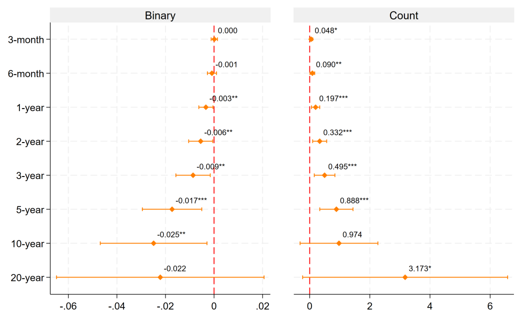
Table 1. Main Results

Variable	Event Binary (1)	Event Count (2)	Goldstein (3)	Tone (4)	Mentions (5)	Articles (6)	Sources (7)
Temperature Deviation	-0.022	3.173*	-50.296	-46.644	-10.949	-0.010	-0.000
	(0.022)	(1.739)	(175.355)	(169.283)	(33.403)	(0.017)	(0.001)
Precipitation Deviation	0.001	0.127*	-0.781	-0.920	-0.154	-0.001	-0.000
	(0.001)	(0.067)	(9.364)	(9.156)	(1.733)	(0.001)	(0.000)
N	233,820	63,756	63,756	63,756	63,756	63,756	63,756
Controls	YES	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES	YES	YES

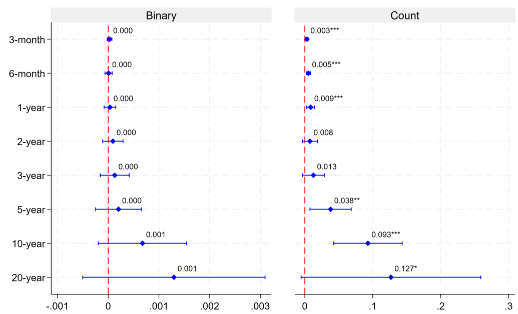
Notes: District-clustered robust standard errors in parentheses. Temperature and Precipitation refer to 20-year rolling average deviations from the 1895–1914 district-level baseline. Model (1) uses a logit regression; Models (2)-(5) use truncated Poisson regression; and Models (6) and (7) use fractional logit regression conditional on event count above 0. Reported coefficients are marginal effects. *** p<0.01, ** p<0.05, * p<0.1.

to — i.e. Recency Bias (Jones et al., 2020).

In Figure 1, we examine different aggregate time windows, averaging our climate change variables over 3 months and 6 months, as well as 1, 2, 3, 5, 10 and 20 years prior to the month in question to test the recency effect. If recency bias holds, the shorter average windows should have larger, more significant coefficients. Instead, we find that the effects decrease in size and significance with shorter-range averages closer to the protest event month. The magnitude of the coefficients increases consistently with the longer-term averages in most of our scenarios up to the 5- or 10-year averages. The confidence intervals expand with longer-term averages, and at the 20-year average, the effect of temperature change on the extensive margins becomes statistically insignificant. Though the coefficients on the effects of precipitation and temperature deviation on protest event count (conditional on an event occurrence) remain statistically significant at the 10% level, the confidence intervals cross the 0 threshold, reducing trust in the strength of the effect.



(a) Temperature Deviation



(b) Precipitation Deviation

Notes: Marginal effects coefficients and 95% confidence intervals are shown for a series of models in which the temperature and precipitation variables are replaced with differing time-averaged deviation values. The periods refer to rolling average seasonally-adjusted deviations from the 1895–1914 district-level baseline. The binary models use logit regression; count models use truncated Poisson regression for counts above zero. All models contain district and month-year Mundlak variables to simulate fixed effects, and controls. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Recency Effect of Temperature and Precipitation Deviation

The increased uncertainty with respect to long-run climate change measures could result simply from fewer long-run averages yet displaying higher deviation levels, or also from the adaptive capacity of some people or regions, the effect of a shifting baseline syndrome (when people's expectations of normal climate shift over time), or the increasing difficulty of observing long-run average changes (assuming the stronger observed effects under the 5- to 10-year averages are at least in part caused through the "conscious" pathway discussed above).

Therefore, we conclude that temperature and precipitation deviation do matter to the likelihood of protests occurring and the number of events conditional on occurrence, and that this effect is strongest over 5- to 10-year averages. As temperature deviation increases, the probability of a protest in a given month decreases, but when an event does occur, the number of protest events increases. We find no evidence that precipitation deviation has an effect on the probability of a protest occurrence in a given month, but conditional on a protest occurring, the number of expected protests increases with higher precipitation.

4 Robustness and Limitations

4.1 Protest Event Data Validation

GDELT is used by numerous studies either as the primary source of events data or in comparison or combination with other datasets, e.g. Manacorda and Tesei (2020). Nevertheless, the use of GDELT in research has attracted considerable scrutiny (Althaus et al., 2021; Hoffmann et al., 2022; Ward et al., 2013). Drawing from these critiques, we classify the risks of systematic errors in our dependent variables, based on the GDELT dataset into three categories: Missing Events — a true event is not recorded in the dataset; False Positives — an event is recorded at a location and on a given date where none occurred (including duplicate records for the same event); and Misclassified Events — a true event is recorded on an incorrect date, at an incorrect location, or wrongly categorised by event type or tone.

We argue the use of GDELT is appropriate for our research question because it is the most comprehensive dataset available to cover the United States over a sufficiently long period to capture variation in long-run climate change. We also accept the conclusion that GDELT is less prone to missing events due to its inclusion of a vast array of news sources (Manacorda and Tesei, 2020). Studies critiquing GDELT have focused on cross country panels, and case studies of countries such as Afghanistan and Nigeria. Our scope limited to the USA likely reduces media coverage biases that would differ in cross country panels, and focuses on a media-rich environment (Lehman-Wilzig and Ungar, 1985).

GDELT's automated coding is susceptible to recording non-genuine protest events, including a failure to group multiple sources into a single event (Manacorda and Tesei, 2020). For example, the maximum protest event count in a district-month is 5737. This is implausible and likely represents duplicate reports of the same events. We manually collapse events listed as occurring on the same day, in the same location, and the same event category into a single record, following (Hoffmann et al., 2022).[4] This reduces the total number of protest events from 885,748 to 345,358. Second, in addressing false positive events, we can approximate the capture-recapture logic of Hendrix and Salehyan (2015) by excluding events with only one article as the source, retaining 330,110 protest events.

4.2 Spatial Autocorrelation

Studies of spatial phenomenon can be challenged if the units display spatial autocorrelation (Lee and Rogers, 2019). Salehyan (2014) cautions that there is little reason to believe that local climate conditions will correlate directly with protest in the same localised area, given the potential for spillovers. To assess whether protest activity exhibits dependence across neighbouring areas we employ Moran's I (Moran, 1950).

We calculate a Global Moran's I value, based on a distance-based spatial weights matrix the statistic, by year-month and compute the mean value to account for the panel structure of our data (Beenstock and Felsenstein, 2019).[5] The centred mean Moran's I value is 0.004, indicating no globally consistent spatial autocorrelation in our dataset.

While the global mean approach can identify clustering across districts based on nearness, our results must still be interpreted cautiously. Temporal heterogeniety within the global mean exists. Additionally, the lack of overall spatial autocorrelation does not preclude the influence of more distant processes. Moreover, people may move because of climate change, and they may also migrate to other locations to protest (Abrahams and Carr, 2017), though US Census Bureau statistics indicate that 97% of the population remains in a district year-to-year, so we do not believe migration introduces a significant source of bias (Kerns-D'Amore et al., 2023).

[4] We sum the count of mentions, articles and sources, and compute an article count-weighted average of the Goldstein and Average Tone.
[5] We test on the logit residuals as the truncated Poisson residuals could bias estimates by excluding observations.

5 CONCLUSIONS

This paper sets out to establish a conceptual framework for climate change as a determinant of protest behaviour, and to stimulate further research into the underlying relationships and specific mechanisms. We offer a novel panel dataset of protest measurements, climate change variables, and socio-demographic indicators covering congressional districts by month across the contiguous United States from January 1979 to December 2023. We discuss empirical evidence of significant aggregate-level relationships between climate change and subsequent protest behaviours. Using hurdle models, our preliminary findings suggest a dampening effect of medium-to-long-run climate change on protest occurrence but an amplification of protest frequency conditional on occurrence. We acknowledge important limitations that cannot be fully addressed in this study. Particularly, despite modifications for robustness, event data biases introduced by media coverage or automated data generation procedures may persist. Finally, while we examine spatial autocorrelation and migration threats that we determine have limited global effects, their influence may introduce heterogeneity. Therefore, this study serves as a starting point, encouraging further investigation on disaggregated effects by context, examination of causal mechanisms, and the incorporation of diverse methodological approaches to fully grasp the complex dynamics between climate change and collective political behaviour.

ACKNOWLEDGEMENT

The authors acknowledge the contributions of Habib Rahman and Ruhul Salim, who were instrumental in the commencement of this research. This work was supported by 1) Pawsey Supercomputing Research Centre's Nimbus Research Cloud resources, with funding from the Australian Government and the Government of Western Australia; 2) the ARDC Nectar Research Cloud, supported by the NCRIS-funded Australian Research Data Commons (ARDC), and 3) an Australian Government Research Training Program (RTP) Scholarship.

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