A multilevel Bayesian framework to analyze climate-fueled migration and conflict

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Abstract

Do climate conditions and extreme events fuel conflict and migration? This question is of growing interest given increasingly dire climate change projections. It is commonly addressed in causal studies that leverage natural experiments by using a multivariate linear regression model with fixed effects. We show that in the climate-migration-conflict nexus, the features of the data generating process and the implicit prediction motivation can lead to a substantial departure from the assumptions of the typical linear reduced form model,challenging the reliability of inferences. We propose a unifying hierarchical Bayesian framework for inferences from the same natural experiments, and describe its benefits for internal and external validity and for analyzing the heterogeneity in response to climate. Using a conflict dataset representative of the literature, we illustrate the misleading results that can ensue from the typical approach and the advantages of the hierarchical Bayesian framework.

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1 Causal inference for effects of climate on conflict and migration

Do climate conditions, and especially climate extremes, fuel or even lead to conflict and migration? This question has been addressed by a rapidly growing number of empirical studies over the past two decades, with contributions from a variety of disciplines. Systematic reviews of the literature have followed, assessing both the diversity of methods used to analyze the statistical relationship between climate and social instability, and whether a consensus emerges.[1] Many find mixed evidence of specific climate impacts, notably due to the variability of specifications and data — such as how the onset of civil war is defined, or which types of displacement are considered (Beine and Jeusette, 2021; Berlemann and Steinhardt, 2017; Ide et al., 2016; Koubi, 2017; Neumann and Hilderink, 2015; Sakaguchi et al., 2017)[2] — while a subset of studies that fit into the new climate-economy literature (Dell et al., 2014), and use reduced-form approaches with plausible exogenous variation in climate variables to identify causal effects, suggest a global pattern of an effect of climate on conflict (Burke et al., 2015; Carleton et al., 2016; Hsiang and Burke, 2014).

The research designs that leverage such natural experiments claim to credibly identify causal effects, and are expected to be important for addressing the new questions that emerge in the climate-migration-conflict nexus. This is of increasing relevance as historically rare climate conditions become more frequent, and adaptation becomes a more salient concern. At the same time, this research area departs substantially from the statistical context that motivates the typical linear reduced form model, in at least two important ways. First, more than in other settings, multiple aspects of the data generating processes diverge from the assumptions of the typical linear model, such that the best linear approximation to the conditional expectation function may not provide the desired information. Second, causality questions in this area are ultimately motivated by prediction — the causal effects of climate on conflict and migration are of practical interest as we expect global changes in the distribution of climate — and indeed causality studies often make implicit or explicit prediction statements. The predictive ability of the models that generate these causal estimates is therefore of interest. Modeling the heterogeneity of climate effects, e.g., across locations in the case of longitudinal data, will further support both explanation and prediction.

The climate-migration-conflict nexus is thereby particularly suited to considering a modeling framework that extends common causal inference methods by incorporating key features of the data and supporting predictive performance.

This paper proposes an alternative to the typical reduced-form linear models to analyze climate-fueled migration and conflict. We first describe the specific features of the data generating process that make for a substantial departure from the assumptions of the fixed effects linear model. We then motivate the concern for the predictive ability of causal inference models in this area, and the interpretation of causal estimates. This leads us to propose a unifying hierarchical Bayesian framework, which has proved its worth in other settings, for inferences from the same natural experiments. We finally illustrate its potential in this setting by applying it to a dataset representative of the literature and comparing the results to those from the fixed effects linear model.

2 Limited applicability of the fixed effects linear model

Research designs with natural experiments and correctly-specified adjustments for confounders typically use a reduced-form linear model to identify an average treatment effect. With longitudinal data, variation in climate variables is leveraged with a multivariate linear regression model including indicator variables

[1] At least 10 systematic reviews of the literature on climate and migration, and 7 such reviews on climate and conflict (not counting responses to the reviews) were published between 2013 and 2021. Migration: Beine and Jeusette (2021); Berlemann and Steinhardt (2017); Cattaneo et al. (2019); Fussell et al. (2014); Kaczan and Orgill-Meyer (2020); Klaiber (2014); McLeman (2013); Neumann and Hilderink (2015); Rigaud et al. (2018); Zanhouo and Nana (2019); conflict: Burke et al. (2015); Carleton et al. (2016); Hsiang and Burke (2014); Ide et al. (2016); Koubi (2017); Sakaguchi et al. (2017); Theisen et al. (2013).

[2] A brief overview of the panel of methods is provided in Appendix A.1.

or "fixed effects" for each location in the sample, as well as eventually time fixed effects, to estimate the average effects of the climate variables across locations. The multivariate linear regression model with fixed effects (MLR-FE) has the following general form:

$$y_{it} = \mathbf{W}'_{it}\beta + \mathrm{X}'_{it}\delta + \phi_i + \psi_t + e_{it}, \qquad e_{it} \overset{\text{iid}}{\sim} \mathcal{N}(0, \sigma^2) \tag{1}$$

where y_{it} is the outcome variable for location i at time t, $\mathbf{W}_{it}$ is a vector of climate variables considered as treatment (generally linear, although specifications sometimes include polynomial functions), X_{it} is an optional vector of adjustment variables, ϕ_i is a vector of location fixed effects, and ψ_t is an optional vector of time fixed effects. The vector of key parameters of interest β is estimated either by maximum likelihood, with the explicit assumption of normally-distributed errors e_{it}, or by least squares — where the same assumption is implicit for the typical tests of statistical significance. The motivation for spatial and eventually temporal fixed effects is to adjust for time-invariant and space-invariant unobserved confounders, respectively.

Assuming a strong identification strategy, such that the slope parameter estimates are unbiased, conditional on the ability to adjust for all confounders, the validity, individual interpretation, and assessment of significance of these estimates still rely on the modeling assumptions of additivity, linearity, spherical errors, normally-distributed errors, and non-collinear regressors (Gelman et al., 2020, ch. 11). Evidently, no assumption is ever expected to be met perfectly with real-world data; however, in the climate-migration-conflict nexus, the features of the data generating process often suggest particularly large departures from the assumptions of the MLR-FE model:

- *Nonlinear functional forms.* Migration or conflict outcomes often have nonlinear relationships to environmental conditions, with threshold effects (McLeman, 2018). In that context, the simple linear approximation to the conditional expectation function, even if accurate in capturing an average relationship, would fail to capture nonlinearities and thereby severely limit, if not mislead, the information carried by the slope coefficients.
- *Limited outcome data.* The range of possible values of measures of migration or conflict is often limited, e.g., as they take the form of counts or binomial outcomes of rare events, which is likely to lead to a non-normal conditional distribution of the outcome. The t-tests underlying assessments of statistical significance of the regression coefficients in the climate-economy literature are robust to departures from normality if the sample size is large enough. However, with highly non-normal errors or small sample sizes — as can be the case with migration and conflict datasets — the results of t-tests may be inaccurate. Short records across a large number of spatial units also raise the risk of high-influence observations, given the presence of extremes of the typically positively-skewed climate variables, or of the highly-skewed outcome variables.
- *Correlated climate regressors.* The regression on several climate variables — such as temperature, precipitation, and indices derived from them, including indices of anomalies with respect to typical levels — limits the simultaneous interpretation of coefficients as individual effects when these variables may be highly correlated.[3] Only their joint effect can be interpreted with confidence, and since the slope estimates are correlated, using t-tests to select just some of the variables may misinform.
- *Hierarchical dependence structures and heterogeneous treatment effects.* Socio-ecological data in the climate-migration-conflict nexus often have a hierarchical temporal, spatial or administrative structure (Neumann and Hilderink, 2015). 'Sandwich' estimators are a common way to adjust the otherwise misleading estimates of uncertainty in the parameters for such dependence (Conley, 1999; Newey and West, 1987). However, the adjustment is only valid to the extent that the dependence structure

[3] The literature does provide some examples of concern of multicollinearity, which is addressed for example by computing the pairwise correlations between the climate explanatory variables (Beine and Parsons, 2015), or by cautioning against the simultaneous interpretation of the regression coefficients (Backhaus et al., 2015).

is correctly specified and the sample is sufficiently large. The MLR-FE model also fits a separate intercept per group and a homogeneous treatment effect, thereby modeling independent baseline outcome levels across groups, while assuming away similar group-level heterogeneity in the effect of the climate variables. This 'no pooling' of intercepts and 'full pooling' of slope estimates corresponds to restrictive assumptions on the role of spatial, serial, or other hierarchical structure in the data generating process.

3 Predictive ability supports causal inferences

Research questions on the statistical relationship between climate change and social instability are often classified as belonging to one of three categories:

1. Forward causal inference, or "what if" questions, which seek to uncover the effects of causes (Gelman and Imbens, 2013), e.g., *What is the average effect of heat waves on migration and conflict?*
2. Reverse causal inference, or "why" questions, regarding causes of effects, e.g., *What are the causes of the increased rates of interpersonal conflict observed in location X in the last few decades?*
3. Prediction, e.g., *How many annual international migrants from region A to region B are expected by mid-century under a global average temperature increase of* $2°C$ *above pre-industrial levels?*

In the heterogeneous body of work concerned with capturing how changes in climate impact conflict and migration, the distinction between these three proximate goals and the focus on different assumptions across disciplines explain in part the variety of statistical approaches. In particular, the divide in stated aims between explanatory and predictive modeling has consequences at every step of the modeling process, from data preparation to model selection by ways of the choice of regressors, while some steps even virtually disappear, such as the evaluation of causal inference models (Shmueli, 2010).

Yet the ultimate motivation of prediction is arguably present in the estimation of climate impacts. This is the case in causal inferences studies in general: Rubin (1974) — the seminal paper presenting the potential outcomes framework, on which typical causal inference methods are based — highlights how the results of a (true or quasi) experiment are generally of interest only to the extent that the observed data are representative of a population of future treatment assignments, i.e., that the causal relationship has a certain predictive ability. This is especially relevant in the case of climate impacts. The answer to *"Do extreme climate events lead to conflict or migration?"* has become an increasing concern under the assumption that it tells us something about *"Will future climate changes bring more conflict or migration?"*

This underlying motivation is revealed by many causality studies themselves, which include predictive statements[4] or pair the estimates from explanatory causal models with climate model output to form projections. In the latter case, Carleton et al. (2016) aptly emphasize the need to account for the multiple sources of uncertainty, namely (i) the statistical uncertainty from the fitted model, (ii) the variation in climate model predictions, and (iii) the potential adaptation of societies to climate change that could alter the response function. We add the concern that the original fitted model might have little predictive power, by using only the climate variables and imposing strong assumptions on unmodeled group-level effects.

Considering the predictive ability of the model would not only support the external validity of the analysis, and address the ultimate motivation of this research, but also bolster its internal validity. Prediction accuracy supports causal inference by providing an additional check on its assumptions: the statistical assumptions about the data generating process and the aforementioned assumption of "subjective random sampling" of trials. Modeling assumptions about the data generating process can be supported either in the pre-modeling phase, by using prior theory to dictate the model, or post-modeling, by testing the model

[4] Few causal studies make explicit statements, most are implicit and answer a question of the type *"Given expected climate change, what does this study imply for the future?"* by positing that if the historical relationship estimated continues, then the estimates suggest that conflict or migration "might" or "will" increase. Some formulate policy recommendations from these predictions, e.g., for adaptation programs or mitigation.

against reality, i.e., assessing its predictive accuracy (Gelman et al., 2004). As social science knowledge can often be too limited for deriving specifications, prediction provides a regime to validate or refute these assumptions ex post.

In summary, the features of the data generating process and the general interest for predictive interpretations of the estimated relationships in the climate-migration-conflict nexus motivate a systematic diagnosis of the assumptions of the fixed effects linear model, and considering more flexible approaches. What inferences would be generated by leveraging the same quasi-experimental variation in climate with a more adjusted modeling and inference framework? The next section proposes to adopt the hierarchical Bayesian framework, easily implementable with common identification strategies, that is a step in this direction. It has the potential to address some of the concerns aforedescribed, by allowing for appropriate conditional distributions for the outcome variable, dependence in the residuals, the modeling of some heterogeneity in the effects of climate, and the propagation of uncertainty into subsequent projections of the outcome under simulated climate conditions from assessment models.

4 A multilevel Bayesian framework

Longitudinal data have a hierarchical structure, where the lower level is the repeated measure within group across time, nested within the higher level which is the group-level data. Recast in a hierarchical modeling framework, the MLR-FE model (1) fit to such data represents specific assumptions on between-group variation: regional intercepts are completely independent or unpooled, while climate variables have homogeneous or fully-pooled effects across regions. This *varying-intercepts fixed-slopes* model is represented in equation (2), where the conditional distribution of the outcome variable is generalized as $\mathcal{F}(\mu, \theta)$ with mean μ and parameters θ, and we take the example of a vector of two climate-related predictors, such that $\beta = (\alpha, \gamma)'$ and $\mathbf{W}_{it} = (A_{it}, B_{it})'$:

$$y_{it} \sim \mathcal{F}(\mu_{it}, \theta), \quad \mu_{it} = \alpha A_{it} + \gamma B_{it} + \mathrm{X}'_{it}\delta + \phi_i + \psi_t \tag{2}$$

In this fixed effects model, each regional intercept is estimated from the data of the given region only, which is equivalent to assuming that they all belong to a joint distribution with an infinite variance. Homogeneous slope parameters, on the other hand, implicitly represent the other extreme: zero variance between regions. Often, it is reasonable to assume some degree of closeness between the effects across regions, and find compromise between full and no pooling of regional coefficients. In effect, we can assume them to belong to a common distribution and let the degree of pooling be determined by the data. This can be implemented with a multilevel model, where within-group variation is explicitly modeled at the lower level, and between-group variation at the higher level. We modify model (2) to allow for the "partial pooling" of both slopes and intercepts across regions, resulting in the two-level model (3), where the vector of region-level coefficients is assumed to follow a joint multivariate normal (MVN) distribution.

To address concerns of bias from time-invariant confounders introduced by the modeled region-level effects, we add group averages of the causal variables as covariates, which enter the model at the higher level[5]

[5]This model is sometimes referred to as the "within-between random effects" model (Bell et al., 2019) or the "correlated random effects" model (Wooldridge, 2012, s. 14.3). By including the group averages as regressors, the problematic correlation between the treatment variables and the group effects is removed from the group-level error term, resolving the concern of bias from group-level (here: time-invariant) confounders similarly to the fixed effects model (Bafumi and Gelman, 2007).

$$y_{it} \sim \mathcal{F}(\mu_{it}, \theta), \quad \mu_{it} = \boldsymbol{a_i} A_{it} + \boldsymbol{b_i} B_{it} + \mathrm{X}'_{it}\delta + \boldsymbol{f_i} + \psi_t$$
$$\begin{bmatrix} a_i \\ b_i \\ f_i \end{bmatrix} \sim \mathrm{MVN}\left(\begin{bmatrix} \alpha_0 + \alpha_1 \bar{A}_i \\ \gamma_0 + \gamma_1 \bar{B}_i \\ \phi_0 \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \sigma_{ab} & \sigma_{af} \\ \sigma_{ab} & \sigma_b^2 & \sigma_{bf} \\ \sigma_{af} & \sigma_{bf} & \sigma_f^2 \end{bmatrix} \right) \tag{3}$$

Beyond relaxing the constraints on the distribution of regional coefficients, the multilevel structure allows them in turn to be informed by group-level predictors. If one observes some marked differences by partially pooling the coefficients, the model can be extended to start analyzing this variation in sensitivity to climate by including relevant variables at the higher level—most simply as predictors of the group-level means. This in turn may aid regional assessments of vulnerability, and improve future predictive capability if changes in these sensitivity predictors were proposed as an adaptation strategy. In this simplest form of the model, the serial or spatial dependence structure is not explicitly represented. Depending on the context, it can be modeled by including relevant additional regressors—such as lags of the dependent variable—alongside X_{it}. The coefficients of control variables X_{it} could be allowed to covary as well.

This model can be estimated within a Bayesian framework, with weakly informative priors assigned to all parameters, including the "hyperparameters" of the between-group covariance matrix. The posterior distributions obtained can then be combined with simulations from climate models to account for the uncertainty from estimation into projections of the outcomes under climate scenarios.

The hierarchical Bayesian framework simultaneously allows for accounting for the typically limited nature of migration and conflict data through an adequate choice of $\mathcal{F}()$, partially pooling the intercept and/or slope coefficients across groups in an efficient way, and propagating the uncertainty in parameter estimates. The same identification strategies based on natural experiments and adjustment for confounders can be leveraged within this framework, which is a generalization of the typical linear model rather than a negation of it. It implies trade-offs, notably an increased computational cost and the potential reduction of the effective degrees of freedom of statistical tests.[6] We propose that when model diagnostics show strong departures from the assumptions of the typical linear model — such that neither the best linear approximation to the conditional expectation function nor t-tests of its coefficients provide relevant information — and when effect heterogeneity and/or prediction are of interest — as is generally the case in the climate-economy literature — these trade-offs may be worthwhile. In the next section, we apply this model to a dataset representative of the literature, and compare the insights obtained to those from the usual fixed effects linear model.[7]

[6] Another trade-off is that of one linear assumption for another. With a *non-identity* link function, bias from time-invariant confounders is fully accounted for by the inclusion of the group average of the causal variable as covariate only if the random effect is a linear function of this average. However, simulations suggest that the bias remains small in most situations (Bell et al., 2019), and one can include additional functions of the group average to characterize more flexible functional forms of the correlation.

[7] Multilevel models have been used to study the relationship between climate and migration. For example, Nawrotzki et al. (2015) use a 2-level regression model to account for the hierarchical structure of their data (households nested in municipalities), while in a similar setting, Nawrotzki et al. (2013) consider a third level and include state-level predictors, explicitly addressing "that migration decisions are influenced by forces operating at different scales". In both studies, the central findings are the variation of the climate-migration association by location characteristics. However, only intercepts are modeled as random effects, slopes are fully pooled across units. The estimated relationships are not causally interpretable by lack of a strong identification strategy, and the predictive ability of the model isn't assessed either. In the context of conflict outcomes, Burke et al. (2015) use a hierarchical Bayesian model to conduct a meta-analysis of estimates from the literature, themselves selected on the basis of their using the MLR-FE framework. We propose instead to use the hierarchical Bayesian framework in combination with established identification strategies, reconciling the focus on identification with the consideration of modeling assumptions. We propose to conduct a heterogeneity analysis by modeling slope parameters in addition to intercepts. Finally, this framework can be adopted not solely in settings with hierarchical levels within the spatial dimension, but with any longitudinal data.

5 Application: Temperature anomalies and civil war in Somalia

We consider the dataset on climate and conflict in Somalia used in Maystadt and Ecker (2014, hereafter M&E). This choice is motivated by the availability and representativeness of these data — their analysis was conducted within the MLR-FE modeling framework, and was referenced in all the literature reviews published since the original publication (Burke et al., 2015; Carleton et al., 2016; Hsiang and Burke, 2014; Ide et al., 2016; Koubi, 2017; Sakaguchi et al., 2017).

The hypothesis originally tested with this dataset is that temperature extremes are an indirect determinant of conflicts in Somalia that operates primarily through the channel of livestock prices. The dataset contains longitudinal, monthly data at the scale of administrative regions (18), over the period 1997–2009. The identification strategy uses the exogeneity of two main variables capturing the level and duration of temperature extremes, and the outcome of interest is the number of violent conflict events. The main variables are listed in Table 1 along with the raw data sources and transformation steps.

Description	Name	Original resolution & processing steps	Source
Number of violent conflict events	*conflict*	region × month	ACLED (2011)
Temperature anomaly or "drought intensity"	TA	0.5° × 0.5° grid × month (average of daily maximum Ts) a. T interpolated to region centers by kriging; b. anomaly computed w.r.t. 1980–2009; c. anomaly averaged over 3 months	CRU TS 3.1 (2008)
Drought length	DL	0.5° × 0.5° grid × month (average of daily maximum Ts) a. T interpolated to region centers by kriging; b. anomaly computed w.r.t. 1980–2009; c. count of consecutive months with positive anomalies	CRU TS 3.1 (2008)
Precipitation anomaly	PA	0.5° × 0.5° grid × month (total precipitation P) a. P interpolated to region centers by kriging; b. anomaly computed w.r.t. 1983–2009; c. anomaly averaged over 3 months	CRU TS 3.1 (2008)

Notes: The dataset also contains livestock prices, instrumented by the climate variables in a two-stage least-squares fixed-effect model to explore the mechanism driving the reduced-form relationship. As this instrumental variable specification adopts the same functional form and treatment of the error terms as the reduced-form, and the present paper focuses on these modeling assumptions, it suffices to focus on the reduced-form model.

Table 1: Main variables in the original reduced-form specification

5.1 Inferences from the MLR-FE model and other single-level specifications

We first estimate the effects of the two climate variables of interest using the MLR-FE model, presented in equation (4), where i refers to the region, m the month of year, y the year, and e_{imy} is the error term.

$$conflict_{imy} = \alpha TA_{imy} + \gamma DL_{imy} + \delta PA_{imy} + \phi_i + \psi_{my} + \omega_{im} + e_{imy}, \qquad e_{imy} \sim \mathcal{N}(0, \sigma^2) \tag{4}$$

Like M&E, we include 18 region fixed effects captured by ϕ_i, 156 month-year fixed effects ψ_{my}, and 216 region-month fixed effects ω_{im}. Temporal and spatial dependencies are accounted for simultaneously by estimating the variance-covariance matrix of the error term following the methods of Newey and West (1987) and Conley (1999) with uniform weighting kernels. Spatial dependency is assumed to disappear beyond a cutoff point of 263 kilometers, corresponding to the maximum distance between the centroids of any pair of neighboring regions, and time dependency is allowed for up to four months. The summary of the results is presented in the first two columns of Table 2,[8] and diagnostic plots of the residuals are

[8]The replication exercise is conducted using the statistical software R. The function `lfe::felm` is used to fit the linear

Error distribution	Normal (original[a] SEs)	Normal (corrected SEs)	Normal	NB	NB	NB
TA	0.71	0.71	0.28	0.01	0.08	−0.00
	(0.25)	(0.37)	(0.18)	(0.12)	(0.11)	(0.11)
DL	0.08	0.08	0.01	0.02	0.02	0.02
	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
PA	−0.47	−0.47	−0.09	−0.08	−0.07	0.03
	(0.20)	(0.31)	(0.19)	(0.16)	(0.15)	(0.15)
$conflict_{lag}$			0.78			0.04
			(0.01)			(0.01)
region FEs	✓	✓	✓	✓	✓	✓
yr-mth FEs	✓	✓	✓	✓	✓	✓
region-mth FEs	✓	✓	✓	✓		✓
N	2,808	2,808	2,808	2,808	2,808	2,808
multiple R^2		0.43				
within[b] R^2	0.17	0.17				
adj. within R^2		0.05				
AIC		16121	13396	5837	5639	5735

[a] The "original" standard errors are those reported in M&E. They were computed using a version of the `ols_spatial_HAC` function by Hsiang (2010a) which miscalculated the weights for serial autocorrelation. Using the corrected version (v3) in the authors' Stata code results in the "corrected" standard errors in the adjacent column.
[b] The within or "projected" R^2 corresponds to the R^2 of the mean-deviated regression, i.e., after removing region fixed effects, and represents the share of the variation in the outcome variable within regions that is captured by the model.

Table 2: Estimates of the single-level model

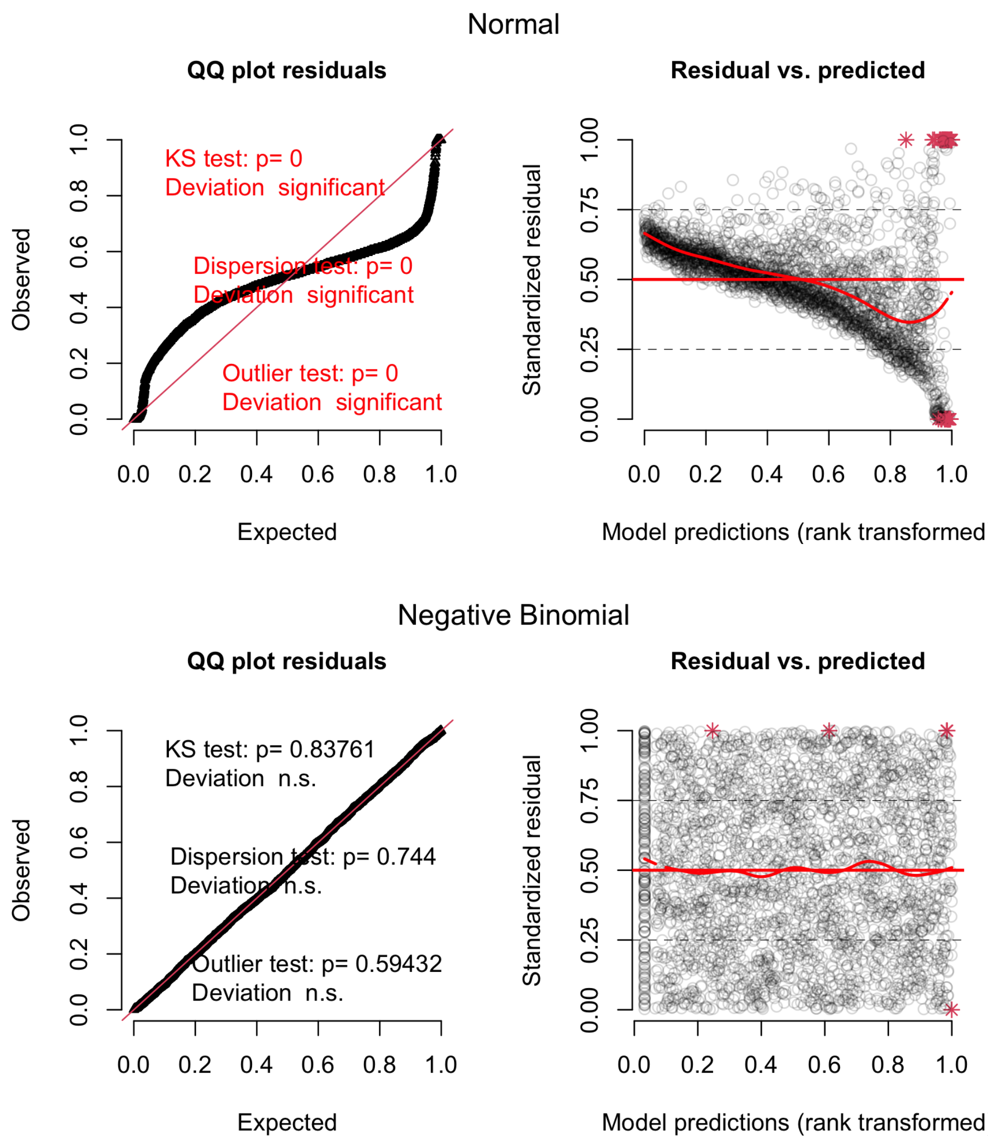
presented in the first row of Figure 1.[9]

The normal quantile-quantile (QQ) diagnostic plot shows a strong departure from normality in the distribution of the residuals. A Shapiro-Wilk test and a Kolmogorov-Smirnov test further confirm that the distribution of the residuals departs substantially from a normal distribution. We also find that TA and DL have a significant Pearson correlation coefficient of 0.28 when fixed effects are removed (Figure A1) — an exploration of the correlations between explanatory variables by region shows that PA and DL are highly correlated in regions 1, 3, 5 and 6. The share of the variation in outcomes within regions that is explained by the model, captured by the *within* R^2, is negligible when adjusted for the degrees of freedom. Given the correlations of TA and DL, the non-normality of the residuals, and the lack of information on the true correlation structure of the residuals, the p-values of the regression coefficients may not be reliable indicators for causal identification.

We therefore explore the robustness of the results to an alternative model specification that seems more suited to the data generating process. We consider a negative binomial (NB) conditional distribution in order to account for the nature of the outcome data, including its positive skew and the frequency of zero values. The second row of Figure 1 presents the diagnostic plots of the NB model, estimated as a generalized linear model with logarithmic link function. The NB appears to be a much more appropriate choice of distribution; the Akaike information criterion is also substantially lower. With this better fitting distribution, we find that the uncertainty around the regression parameters for TA and PA increases greatly

regression. The adjustment for serial and spatial autocorrelation, implemented in the original paper with the `ols_spatial_HAC` function available for Stata by Hsiang (2010b), is implemented by adapting the function `ConleySEs` for R by Darin Christensen (Christensen, 2017; Christensen and Fetzer, 2015).

[9] Additional diagnostic plots are provided in the Appendix A.2.



Notes: Residual plots are obtained with the R package `DHARMa` which uses a simulation-based approach to create interpretable scaled residuals from generalized linear mixed models (Hartig, 2017). It also provides the Kolmogorov-Smirnov (KS) test for the goodness of fit of the residuals to the specified distribution, and tests for dispersion and outliers (represented by red stars in the *Residual vs. predicted* graphs).

Figure 1: Residual plots of the reduced-form model assuming a conditional normal (top) or negative binomial (bottom) distribution.

(Table 2).[10]

Conflict events at the monthly scale are likely to be persistent and thus be temporally autocorrelated. They can therefore be considered as an autoregressive process, informed by both the lagged dependent variable and the exogenous climate predictors. We consider a model that includes this feature of the data generating process explicitly — in place of adjusting the estimate of the error covariance matrix with a weighting kernel — by adding a one-month lag of *conflict* as explanatory variable. We find that the effect of DL is reduced substantially and that the coefficient on $conflict_{lag}$ is the only one that is estimated precisely (Table 2), potentially changing the interpretation of the influence of climate variables from the baseline Gaussian model. Similarly, one could explicitly model the space-time dependence structure of the response variable; such a model is not developed here for conciseness, examples are presented in Bakar and Sahu (2015); Cocchi et al. (2007); Gelfand et al. (2005); Ugarte et al. (2015); Wikle et al. (1998); Wikle and Hooten (2006).

5.2 A multilevel Bayesian model of climate-fueled conflict

We relax the assumptions of no-pooling of baseline effects and full pooling of climate effects across regions by generalizing to the multilevel negative binomial model (5) with partial pooling of both the slopes and intercepts across regions, and we estimate it in the Bayesian framework.[11] Weakly informative priors are assigned to all parameters, including the "hyperparameters" of the between-group covariance matrix.

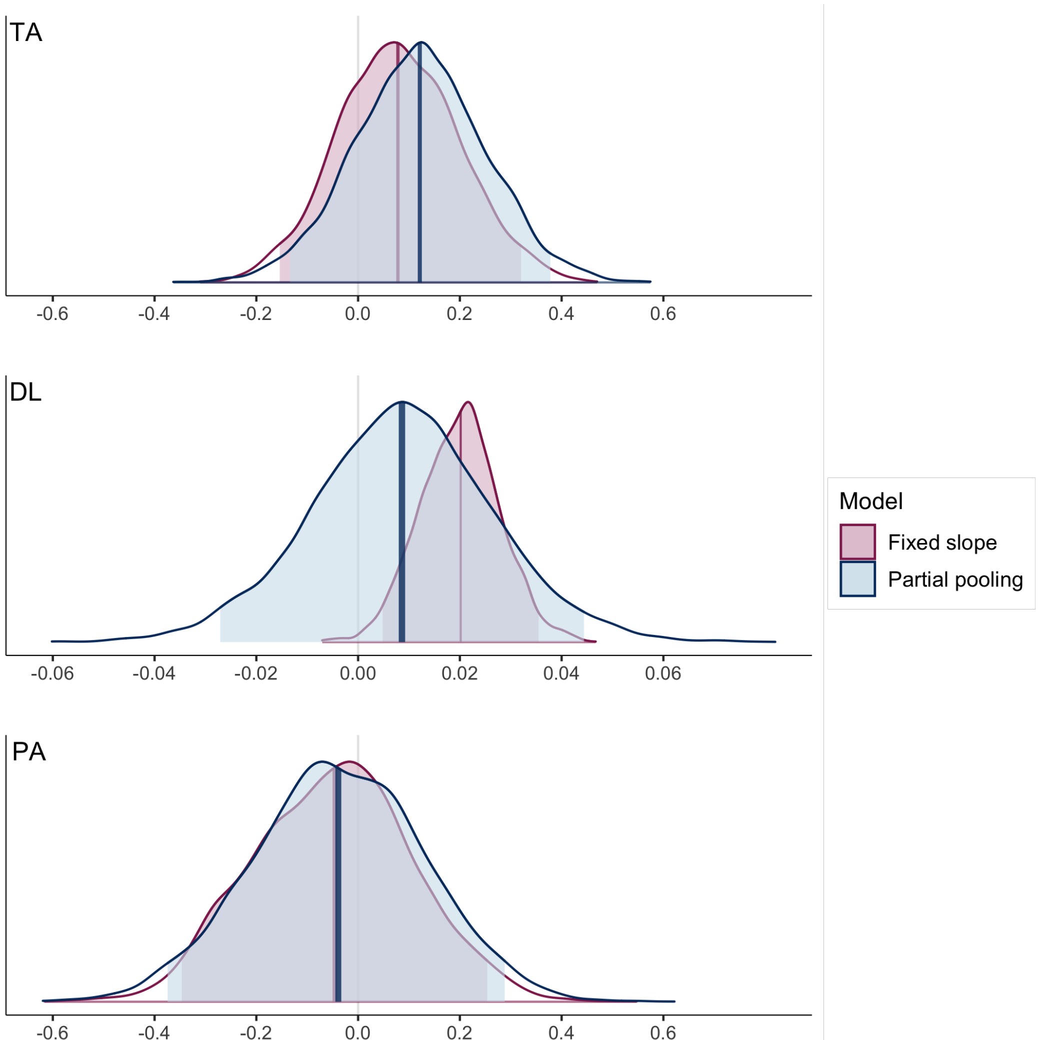
$$
\begin{aligned}
conflict_{imy} &\sim \text{negative binomial}(\mu_{imy}, \Theta) \\
\mu_{imy} &= a_i TA_{imy} + b_i DL_{imy} + c_i PA_{imy} + f_i + \psi_{my} \\
\begin{bmatrix} a_i \\ b_i \\ c_i \\ f_i \end{bmatrix} &\sim \text{MVN}\left(\begin{bmatrix} \alpha_0 + \alpha_1 \overline{TA}_i \\ \gamma_0 + \gamma_1 \overline{DL}_i \\ \delta_0 + \delta_1 \overline{PA}_i \\ \phi_0 \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \sigma_{ab} & \sigma_{ac} & \sigma_{af} \\ \sigma_{ab} & \sigma_b^2 & \sigma_{bc} & \sigma_{bf} \\ \sigma_{ac} & \sigma_{bc} & \sigma_c^2 & \sigma_{cf} \\ \sigma_{af} & \sigma_{bf} & \sigma_{cf} & \sigma_f^2 \end{bmatrix} \right)
\end{aligned}
\tag{5}
$$

Figure 2 shows the posterior distributions of the central slope coefficients of the two negative binomial models — (α, γ, δ) for a single-level model and $(\alpha_0, \gamma_0, \delta_0)$ for the multilevel model (5) — estimated in a Bayesian framework. As expected, the median values of the distributions from the fixed-slope Bayesian model are virtually identical to the frequentist point estimates. However, in the partial pooling model, the distribution of the mean slope coefficient for DL shifts such that the evidence of an effect of the climate variable is inconclusive.

The posterior distributions of the partially-pooled slope coefficients give us some insight as to what drives these higher-order effects. Figure 3 shows a great heterogeneity in the effect of DL across regions, with only a few regions — 9, 10, and 12 — actually driving the positive causal relationship, while others experience negative effects, which helps explain the relatively weak results in the complete pooling model. Regions 9 and 10 are those with the least zero *conflict* values across the study period. Additionally, the strong correlation of the posterior samples of the coefficients for DL and TA (-0.51) is a concern for the attribution of the effect to just one of these variables. The uncertainty of the parameters also shows large differences across regions. In regions 1 and 5 the large uncertainty reflects the low number of conflicts over the study period (one and four conflicts, respectively).

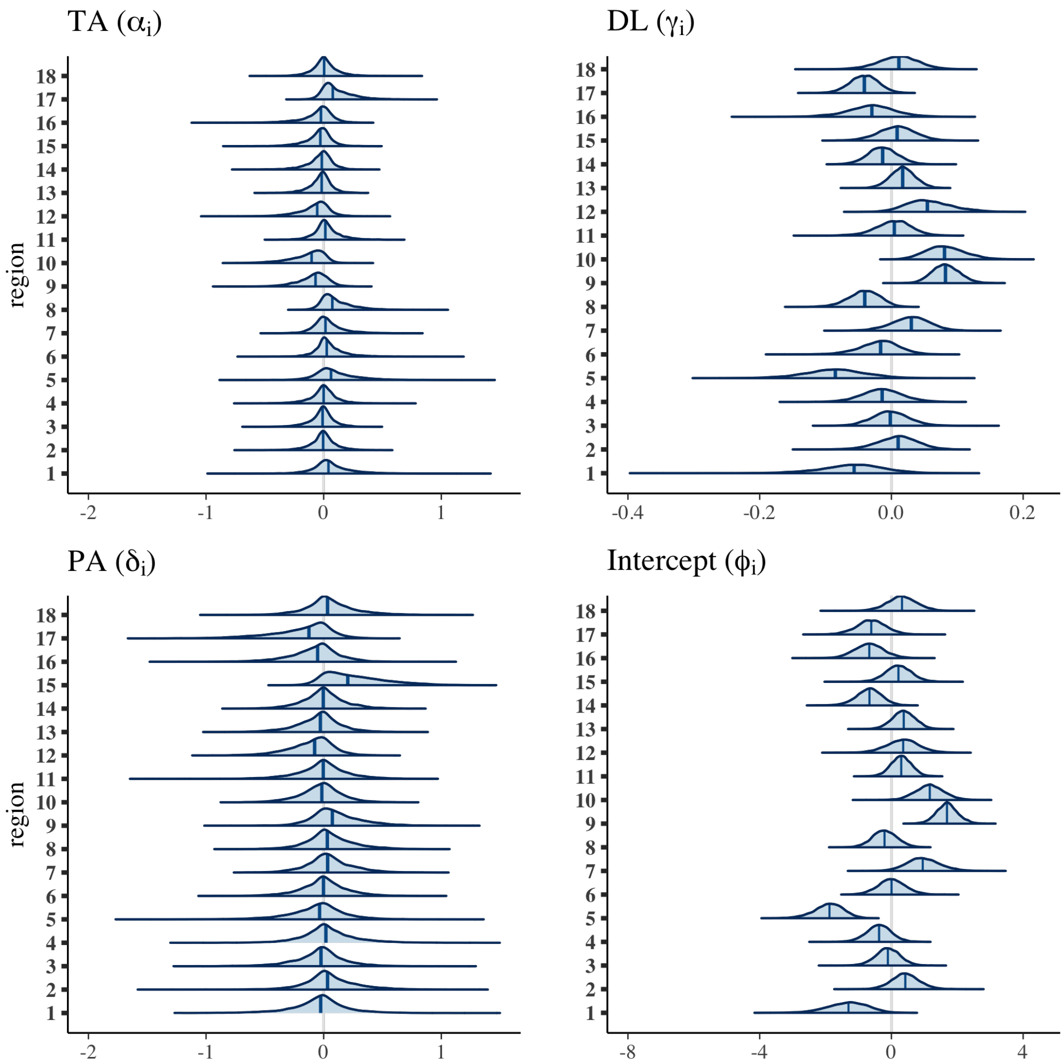
[10] The raw coefficients from the simple single-level NB model are presented in column 5 of Table 2. Note that their interpretation differs to that of those of the Gaussian model: in the normal models, they represent additive changes in y, whereas in the NB model, they represent additive changes in $\log(y)$ due to the logarithmic link function. y corresponds to the number of conflicts — not their probability, as could be implied by the mention of "likelihood of conflicts" in the original publication.

[11] Removing the region-month interaction term ω_{im} present in the single-level model specifications gives comparable results and is more computationally efficient, we therefore remove it from the multilevel model for simplicity.



Notes: The Bayesian models are fitted using the R package `rstanarm` (Goodrich et al., 2020). Posterior distribution plots are obtained with the R package `bayesplot` (Gabry and Mahr, 2021). 95% uncertainty intervals are shown as shaded areas under the curves around the median point estimates.

Figure 2: Posterior distributions of the central slope coefficients of the Bayesian NB models. Pink: single-level model (varying-intercept, fixed-slope), parameters α, γ, δ. Blue: two-level model (intercepts and slopes partially pooled across regions), hyperparameters $\alpha_0, \gamma_0, \delta_0$.



Notes: Posterior distribution plots are obtained with the R package `bayesplot` (Gabry and Mahr, 2021). 95% uncertainty intervals are shown as shaded areas under the curves around the median point estimates.

Figure 3: Posterior distributions of the partially pooled region-specific intercepts and slope coefficients (model 5).

The application of the hierarchical Bayesian model to (M&E)'s dataset illustrates how the standard MLR-FE model can be readily recast in the hierarchical Bayesian framework, with a better suited conditional distribution for the response variable, inferences on parameters generated using simulations—which enable the propagation of uncertainty if the estimates are then used in projections—and the partial pooling of regression coefficients, and can thereby allow one to analyze and model differences across groups efficiently. The posterior distributions obtained can easily be combined with simulations similar to those proposed in M&E, e.g., of increases of one standard deviation in the main climate variables,[12] or of projected changes from global climate models under established climate scenarios, to address what we can reasonably answer to questions akin to *Will future climate changes bring more conflict or migration?* and with how much uncertainty.

6 Discussion

In the context of climate-fueled migration and conflict, some statistical principles ring particularly true:

- Prediction and identification of causal effects are complementary pursuits. Together, they support the modeling assumptions and thus the internal validity of the statistical analysis, and give weight to its external validity which is generally of practical interest. Reporting both the model's explanatory power and its predictive power, and considering the latter for model selection, may strengthen the inferences from natural experiments (Shmueli, 2010). One example of a unifying approach to causality and prediction is in accounting for the spatiotemporal dependence structure often present in the dynamics of both the response variable and regressors. While such dependence in the outcome can be accounted for by adjusting the estimate of the error covariance matrix — assuming the corresponding "sandwich" estimator is correctly specified — it could also be explicitly incorporated into the model. Emerging deep learning approaches may provide effective solutions for addressing such spatio-temporal data sets, with the caveat that typically large sample sizes are needed.
- The linear approximation of the conditional expectation function of the outcome that is the target of the linear reduced-form model may be misleading when the data generating process departs substantially from the modeling assumptions. Separately from the identifying assumptions supported by quasi-experimental variation and the ability to adjust for confounders, the validity of inferences also rests on the underlying assumptions of the model estimated. An assessment of the key assumptions such as the conditional distribution of the outcome, the absence of high influence observations, and the noncollinearity of regressors, can be presented with simple diagnostic plots—see for example Cohen et al. (2008).
- The response to climate variables may be quite heterogeneous across spatial units, yet the ability to estimate spatial sensitivity may be limited by the sample size. In such cases, a fully pooled model for the slope coefficients, as is typical in the MLR-FE framework represents a trade-off between the efficiency gained by using a larger sample size (by pooling across all locations) and the potential bias at each unit. Generalizing to a partial pooling strategy can lead to efficiently combining information across units, shrinking the uncertainty and reducing the bias at individual spatial units. As one strives to understand the determinants of variations in the response to climate, a multilevel model provides the structure for efficient estimation of treatment heterogeneity and exploration of the potential physical and socioeconomic factors of differences in the sensitivity to climate extremes. The typical MLR-FE model corresponds to an extreme end point of the suggested multilevel model. Partial pooling relaxes the assumptions according to the data, and provides a structure to explore the sensitivity to climate as well as the "fixed effects", in a way that is useful when considering projections.

[12] The regional correlation of climate variables which hinders the individual interpretation of their coefficient estimates would also constrain the changes that can reasonably be simulated. In some cases, highly-correlated treatment variables could be replaced by the various climate indices proposed in the literature to characterize the different types of climate extremes.

We propose to adopt the unifying hierarchical Bayesian framework that is a generalization of the linear reduced-form model, and can address the three concerns above, thereby strengthening the inferences from natural experiments in the climate-migration-conflict nexus.[13] The benefits of such models and inference methods have been shown abundantly in the statistics literature, and are relevant in most settings using observational data to generate causal and predictive inferences. They come down to considering more general statistical frameworks to learn from quasi-experimental data, and selecting models that try to approximate the data generating process; essentially applying the recommendation of "a combination of the economists' focus on identification strategies and the statisticians' ability to build more complicated models to assess what might happen if the strict assumptions fall apart" (Gelman, 2011). A key point is that through multilevel models, one can explore whether variation in climate sensitivity across groups is important, as well as observed attributes that it may depend on. As the number of settings increases, the uncertainty associated with the group mean coefficient decreases. In the partial pooling framework, the multilevel model, through shrinkage towards a group mean for the group coefficient, or through dependence of individual coefficients on specific group attributes, provides a mechanism for identification of across-group variations, and whether they are significant relative to the group mean coefficient. These benefits are particularly salient for studying the relationship between climate and social instability. By enhancing the internal validity, external validity, and efficiency of the inferences, they seem a promising avenue towards understanding the impacts of changes in climate on social outcomes of interest, while bridging differences between the statistical traditions of disciplines whose collaborative work is needed on such interdisciplinary questions.

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[13] Other promising avenues of research, not explored here as they beyond simple extensions of the MLR-FE framework, include using machine learning methods to uncover the complex functional forms of these causal relationships and select key variables. Schutte et al. (2021) apply random forests and leave-future-out cross validation to study the relationships between climate and asylum migration.

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Appendix

A.1 Dominant statistical methods in the literature

From 16 systematic reviews of the literature published between 2013 and 2021, we identify the different types of modeling and inference approaches used. At the highest level, we can first separate two classes of models:

- Computational models, which use simulations to study systems of interest. These include agent-based models (Hassani-Mahmooei and Parris, 2012; Kniveton et al., 2011), system dynamics models (Ginnetti, 2015), computable general equilibrium models (Barbieri et al., 2010), and integrated models (Krol and Bronstert, 2007).
- Empirical analysis using regression models, from simple least squares to multilevel generalized linear models and nonparametric predictive models.

Regression-based approaches can be classified along multiple dimensions, such as the functional form of the relationship between predictor and outcome variables, the assumed conditional distribution of the outcome variable, and the stated end goal of the statistical exercise — notably prediction or causal inference (which can be considered as conditional prediction). Table A1 illustrates the diversity of approaches as they leverage some combination across these key dimensions, by citing a sample of recent papers in the literature.

A.2 Diagnostic plots of the fixed effects linear model

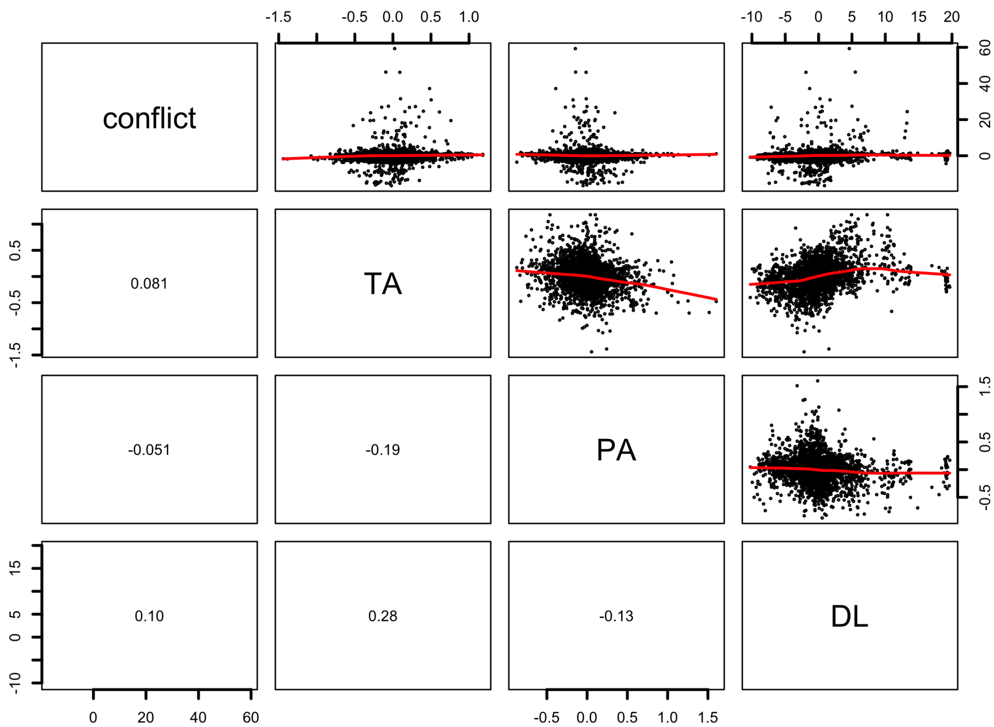
Scatterplots of the model's main variables — adjusted for the region, month-year and region-month fixed effects by using the residuals of a linear regression of each variable on these fixed effects — suggest no obvious strong relationships between the outcome and the explanatory variables (Figure A1).

Influential observations The heteroscedasticity in the residuals raises the concern that a subset of observations may have a disproportionate impact on the coefficients. The *Residuals vs. Leverage* plot shows residuals with high values (up to 15 standard deviations) but not high leverage (Figure A2).

	Backhaus et al. (2015)	Berlemann and Tran (2020)	Caruso et al. (2016)	Hendrix and Salehyan (2012)	Henry et al. (2004)	Maystadt and Ecker (2014)	Nawrotzki et al. (2013)	Nawrotzki et al. (2015)
Pooling of individual effects								
fully pooled (no FEs)			x	x	x			
no pooling (unit/group FEs)	x	x		x		x		
partial pooling (multilevel)							x	x
Partial vs total effect of climate								
reduced form w/o channels		x	x	x	x	x		
disentangle the reduced form relationship	x	x	x			x	x	x
Functional form of the relationship w. the climate explanatory variables								
linear	x	x	x	x	x	x	x	
non-linear				x			x	x
Type of outcome variable								
binary (event)				x	x		x	x
count or flow	x	x	x	x		x		
Goal and use								
association	x				x		x	x
prediction						x		
causal inference		x	x	x		x		
Estimation								
OLS, GLS	x	x	x		x	x		
ML		x		x			x	x
GMM								
Bayesian								
Post-estimation standard error adjustment								
Heteroskedasticity robust	x				x			
Clustering			x	x				
Serial/spatial correlation using a kernel						x		

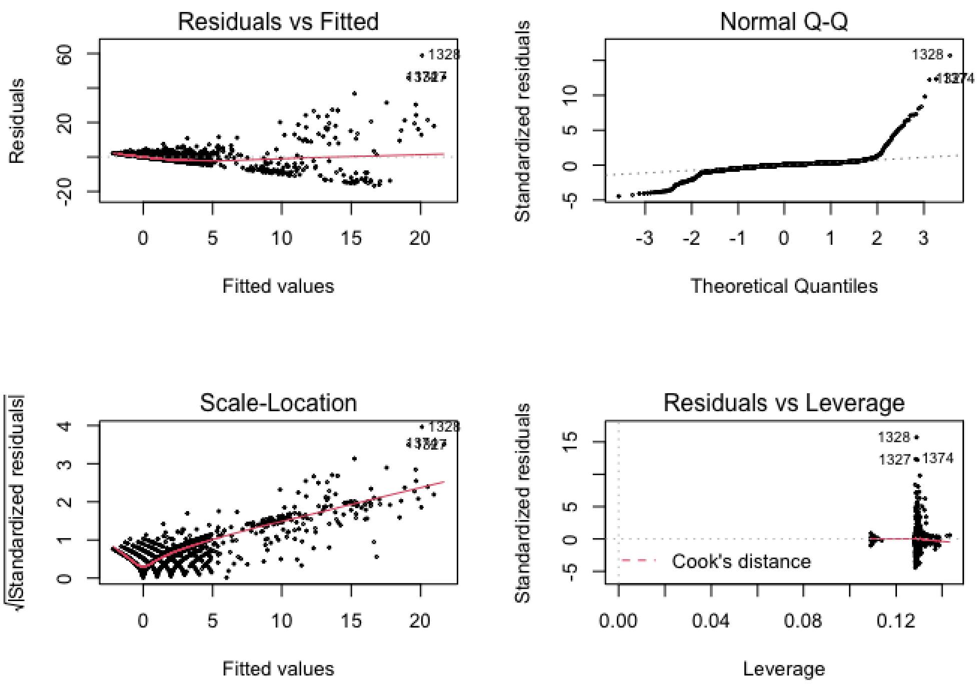
Notes: The studies cited are not selected based on results or rigor (and as such should not be interpreted as a sample of "best studies") but serve to illustrate the varied approaches in the literature. All papers but the most recent, published after 2020, were cited by at least one of the 16 literature reviews.

Table A1: Attributes of regression-based approaches in the climate-driven migration and conflict literature



Notes: Top-panel: LOWESS lines with span=2/3.

Figure A1: Scatterplots and correlations of the main variables after accounting for the region, month-year and region-month fixed effects.



Notes: From left to right, top to bottom: "Residuals vs. Fitted" shows whether the residuals are equally spread around a horizontal line or display a pattern — suggesting a nonlinear relationship that was not captured by the model. "Normal Q-Q" shows how the distribution of the residuals aligns with a normal distribution. "Scale-Location" presents the spread of transformed residuals across the range of predicted values, a uniform vertical spread indicating uniform variance. "Residuals vs. Leverage" highlights influential observations as those outside "Cook's distance lines," i.e., whose Cook's distance (the change in the predicted value if the given observation were omitted) is large.

Figure A2: Diagnostic residual plots of the reduced-form model