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Drought impacts on armed conflict primarily explained by pre-existing conflict risk

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Abstract

Although extensive research has examined climate-conflict relationships, systematic analysis of how climate impacts heterogeneously affect armed conflict dynamics remains limited. Without understanding these heterogeneous effects, our ability to understand and respond to climate-related armed conflict risk remains incomplete. This paper systematically investigates the heterogeneous causal effects of droughts on both conflict incidence (extensive margin) and conflict intensity (intensive margin) across 8 world regions, 4 temporal and spatial resolutions, and 3 conflict types, reporting only patterns that hold consistently across specifications. Using a causal forest and a calibration test for heterogeneity reveals some evidence that droughts heterogeneously affect conflict incidence. Zero inflated negative binomial models that control for grid cell and yearly effects and include drought interactions with socioeconomic, political, and demographic variables show significant evidence that droughts heterogeneously affect conflict intensity. When examining individual interaction terms, baseline conflict risk-estimated using a random forest with the same socioeconomic, political, and demographic predictors plus conflict history-emerges as the only significant source of heterogeneity that is consistent across specifications. This suggests that other variables primarily influence drought–conflict relationships through their contribution to overall conflict risk, rather than through independent causal channels. The results demonstrate that even when droughts do affect conflict intensity heterogeneously, their overall role in armed conflict dynamics remains limited.

1. Introduction

The world is currently on track to exceed 2 °C of warming, which implies significantly more frequent and severe extreme weather events, ecosystem disruption, and threats to human security [1–3], at the same time that armed conflict (referred to hereafter as 'conflict') is hovering around record levels [4, 5]. While climate impacts typically have modest direct effects on conflict, these effects exhibit substantial heterogeneity-meaning that the same climate shock can have dramatically different effects on conflict outcomes across different socio-economic, political, and environmental contexts [3, 6]. Understanding this heterogeneity is crucial for developing effective strategies to address conflict risks in a warming world.

Researchers have identified numerous sources of heterogeneity that shape how climate hazards affect conflict, including ethnic or religious divisions [7–9], agricultural conditions [10, 11], institutional capacity [3, 12], social capital [13], and strategic contexts [14]. However, each of these studies examines only one or a few sources of heterogeneity in isolation. This fragmented approach creates three key gaps in our understanding. First, it remains unclear which sources of heterogeneity are most important for explaining variation in climate-conflict relationships. Second, there is limited evidence about whether findings from individual studies generalize beyond their specific contexts. Third, the overall magnitude of climate effects on armed conflict-after accounting for contextual variation-remains somewhat ambiguous.

Using drought as a key climate impact, this analysis addresses these gaps by examining three fundamental questions: *Is the relationship between droughts and armed conflict heterogeneous?* If so: *what are the most important sources of heterogeneity? And how important is this heterogeneity for understanding armed conflict dynamics overall?*

Two factors motivate this analysis's focus on droughts. First, the Intergovernmental Panel on Climate Change (IPCC) identifies droughts as particularly concerning for increasing intrastate conflict under continued warming [3]. This is largely because drought conditions affect incomes from agriculture as well as water and food security, which can lead to violence [15–18]. Second, while research has shown that large-scale disasters can heterogeneously affect conflict intensity [14], no systematic investigation has examined such heterogeneous impacts for more frequent but lower-intensity climate events like droughts.

This study examines the heterogeneous ways that droughts affect armed conflict by estimating the causal impact of droughts on both conflict incidence ('is there a conflict?') and conflict intensity ('how many casualties occurred?'), then exploring how these effects vary across different contexts and conditions. The research estimates the causal effects of drought on the extensive and intensive margins of conflict using two complementary methodological approaches designed to capture treatment effect heterogeneity. First, a causal forest model estimates how drought affects conflict incidence and is specifically designed to explore treatment effect heterogeneity [19]. Second, a zero-inflated negative binomial (ZINB) machine learning model examines drought's impact on conflict intensity by separating the extensive margin (conflict incidence) from the intensive margin (conflict intensity), enabling precise estimation of how droughts affect conflict intensity [20–22]. The ZINB analysis incorporates spatial and temporal controls to improve identification of the causal relationship between drought and conflict while controlling for confounding factors.

Previous studies typically examine one or a small set of potential contextual factors that may influence climate-conflict relationships. Scholars have attempted to synthesize these findings through literature reviews [23–27]. Such reviews effectively map current knowledge and research progression [28], but face two critical limitations. First, they identify relevant contextual factors without quantifying their relative importance. Without a sense of proportion about the extent to which different political, economic, and social conditions shape the climate-conflict nexus, there is a risk of allowing opportunistic, simplistic, or exaggerated claims about how climate change impacts conflict to take root [29], which can lead to ineffective or harmful policies [30]. Second, literature reviews cannot systematically assess whether findings generalize across different regions, conflict types, and units of analysis—a crucial limitation given potential publication bias and the need to identify which results are most relevant for broader policy applications and theoretical understanding [31].

This paper addresses these challenges and makes three key contributions to the existing literature. The first contribution addresses a critical methodological gap in climate-conflict research. While quantitative conflict studies typically analyze either conflict incidence (e.g. [7, 32]) or intensity (e.g. [14, 33]) separately due to their distinct drivers [34], this analysis examines both outcomes simultaneously. This integrated approach is particularly valuable given the IPCC's assessment—assigned low confidence—that climate impacts may more strongly influence the dynamics of ongoing conflicts than the initial outbreak of new conflict [3]. By analyzing conflict incidence and intensity together, this study provides a rigorous test of whether one important climate impact, droughts, affects conflict incidence versus intensity differently, contributing to resolving this key uncertainty in the literature.

Second, while previous research has typically examined only one or two factors that might influence how climate affects conflict [8, 9, 11], or has relied on expert opinions rather than data analysis [6], this study takes a more comprehensive approach. The analysis estimates how drought affects conflict, then systematically tests how this relationship varies across many different contextual factors-such as economic conditions, governance quality, and demographic characteristics. This systematic approach provides empirical evidence for determining which factors most strongly shape how drought leads to conflict. Previous studies often focused on just a few variables or only reported statistically significant results, leaving critical gaps in understanding when and where climate-conflict relationships are strongest.

Finally, this study addresses the challenge of generalizability in climate-conflict research, where different methodological choices often yield contrasting results [6, 35]. The analysis systematically examines drought–conflict relationships across multiple dimensions: different conflict types, geographical regions, temporal resolutions, and spatial resolutions. Examining results across varying spatial resolutions helps reduce the risk that findings stem from aggregation bias [32, 36]. By reporting only findings that persist across these varied specifications, the approach helps distinguish robust patterns from potentially spurious or context-specific results. While Burke *et al* [37] employ a similar meta-analytic approach to examine direct effects of climate hazards on conflict, this study focuses on heterogeneous effects. This methodology effectively addresses concerns about publication bias [31] while providing a

comprehensive assessment of which drought–conflict patterns hold consistently across different contexts.

2. Analytical approach

The analysis examines drought–conflict relationships between 1991 and 2015 following the systematic procedure outlined in figure 1. Data are first aggregated to appropriate spatial and temporal scales (section 2.1) by summing conflict events within grid cells, up-scaling some variables to match grid resolution, and down-scaling others from national to grid cell levels. The analysis then uses separate procedures to estimate causal effects of drought on conflict incidence and on conflict intensity (sections 2.4 and 2.5). These causal effect estimates enable systematic investigation of heterogeneous treatment effects to address the three research questions (section 3).

To ensure robustness, the analytical framework examines multiple dimensions: 8 geographical regions, 4 spatial resolutions, 3 types of conflict, and 14 temporal specifications (see figure 1). This comprehensive approach recognizes that drought–conflict relationships may manifest differently across various scales and contexts. The temporal specifications are particularly important, as they capture both immediate and delayed effects of drought on conflict[4]. This flexible temporal structure allows the analysis to identify both rapid onset and longer-term impacts of drought on conflict. While this multidimensional approach theoretically yields 1344 possible specifications, not all combinations produce viable results due to ZINB model convergence issues (section 2.4.2). The framework serves two key purposes: validating the robustness of findings across different modeling choices and identifying consistent patterns in how drought's effects vary across different conditions.

2.1. Data

2.1.1. Outcomes

The selection of drought and conflict indicators prioritizes coverage and comparability [5]. Conflict data comes from the Uppsala Conflict Data Program's (UCDP's) Georeferenced Event Dataset [5, 38], which uses a standardized data collection methodology to record conflict events worldwide separated into state-based, non-state, and one-sided (OS) violence. The UCDP dataset provides standardized, globally comparable data commonly used in climate-conflict research [39, 40]. Nevertheless, UCDP does not capture armed conflict events where no one dies, is more likely to report events taking place in urban areas, and fatalities may be an imperfect measure of the intensity of a conflict [5, 38]. This is a limitation of this study, as well as most studies relying on major conflict data sources.

The selection of drought- and conflict-related indicators prioritizes coverage and comparability [5]. Conflict data are drawn from the UCDP's Georeferenced Event Dataset [5, 38], which employs a standardized data-collection methodology to record conflict events worldwide, classifying them into state-based, non-state, and OS violence. The UCDP dataset provides standardized, globally comparable data that are widely used in climate-conflict research [39, 40]. Nonetheless, the UCDP does not capture armed-conflict events in which no fatalities occur and tends to under-represent events occurring in rural areas. Furthermore, fatalities are an imperfect measure of conflict intensity [5, 38]. This limitation applies to the present study as well as to most research that relies on major conflict-data sources.

Each conflict event includes geographical coordinates and estimated fatalities, making conflict incidence and intensity inherently dependent on spatial and temporal resolution. Different resolutions capture distinct aspects of conflict patterns—for example, analysis at 5° grid cell years typically shows more conflict events than analysis at 0.5° grid cell months. This variation motivates examining multiple spatial and temporal scales to ensure robust understanding of conflict dynamics.

2.1.2. Treatment

This study defines drought using the standardized precipitation-evapotranspiration index (SPEI), which has been widely adopted in climate-conflict research [9, 11, 41–43]. SPEI compares current precipitation and evapotranspiration to long-term local averages [44, 45]. A drought occurs when SPEI falls below-1, indicating conditions one standard deviation drier than historical norms for that location and season. This threshold provides enough drought events for robust statistical analysis while focusing on meaningfully severe conditions. Because SPEI is standardized for each location and time period, drought events have uniform probability across space and time. More importantly, SPEI derives solely from climatic variables, providing variation that is independent of the socioeconomic, political, and demographic factors that typically confound conflict studies. This makes SPEI well-suited for causal inference studies.

2.1.3. Covariates

Rather than focusing on the direct causal relationship between drought and conflict, this study examines heterogeneity in that relationship [9, 11, 31]. There

[4] While there are 4 temporal resolutions (1 month, 3 months, 6 months, and 1 year), each resolution generates multiple forward-looking specifications. For example, the 1 month resolution includes five specifications: contemporaneous effects plus predictions at 1 month, 3 month, 6 month, and 1 year horizons. Similarly, the 3 month resolution generates four specifications, the 6 month resolution three, and the 1 year resolution two, totaling 14 temporal specifications.

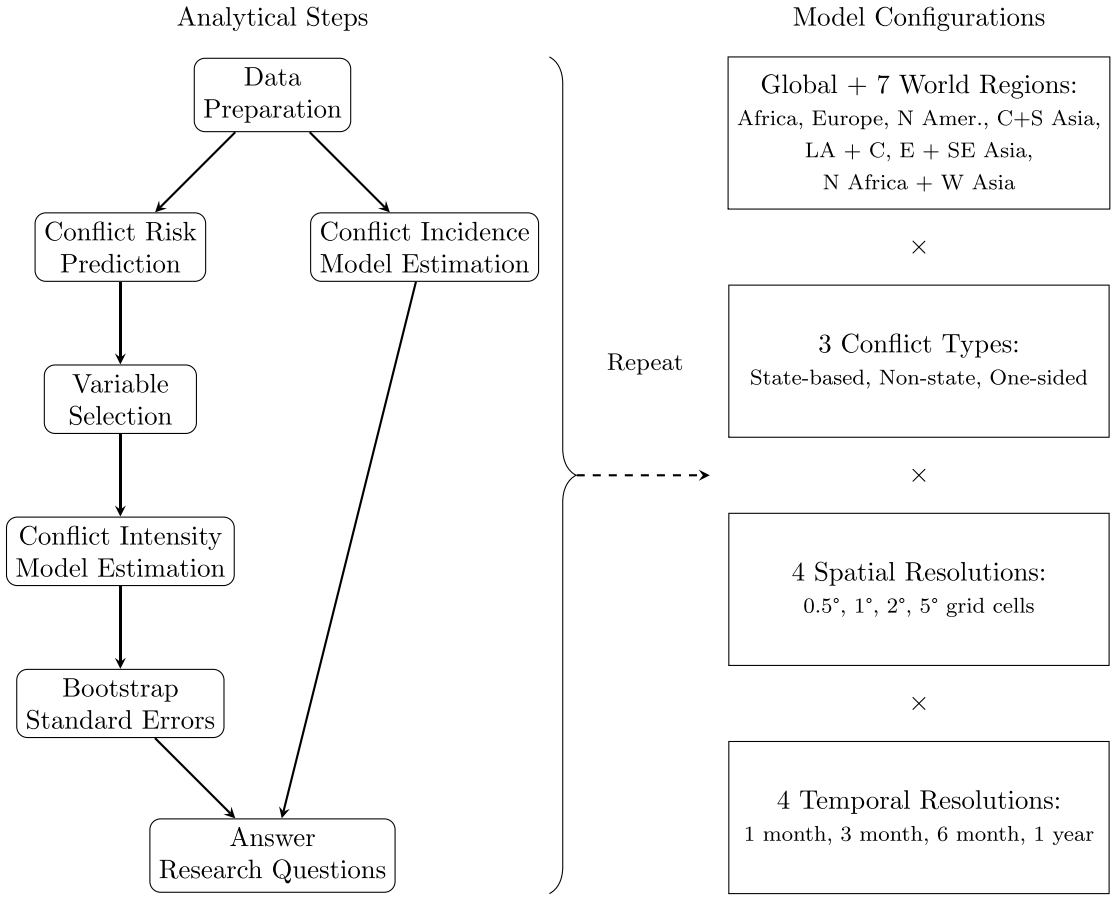

Figure 1. Analysis procedure. The analytical steps panel (left side) shows the sequential methodology. The analysis first aggregates data to appropriate spatial and temporal resolutions (data preparation, see section 2.1). It then follows two parallel analytical tracks: for conflict intensity, the analysis estimates conflict risk using a generalized random forest (GRF) (conflict risk prediction, section 2.2), identifies key variables through boosted regression (variable selection, see section 2.3), applies a ZINB model to estimate how drought effects vary across contexts (conflict intensity model estimation, see section 2.4), and then bootstraps the standard errors to ensure they are robust to spatial and temporal heteroskedasticity and autocorrelation (bootstrap standard errors, see section 2.4.1). In parallel, the analysis tests for heterogeneous drought effects on conflict incidence using a causal forest model (conflict incidence model estimation, section 2.5). The model configurations panel (right side) illustrates how this procedure is systematically applied across different dimensions: conflict types, geographical regions, temporal resolutions, and spatial resolutions. This comprehensive approach ensures robust findings independent of specific modeling choices.

are many plausible ways that socioeconomic, political, and geographic covariates could mediate drought's effects on conflict. This paper evaluates 66 such covariates identified by previous literature as potentially important drivers of conflict dynamics. A complete description of each covariate and data source used in the analysis as well as the handing of missing values is available in section 1 of the supplementary information.

2.2. Estimated conflict risk

The analysis uses a generalized random forest (GRF) to estimate two distinct probabilities. First, the baseline conflict risk ($\Pr(Y_{gt} > 0 | X_{gt}, W_{gt} = 0)$) captures the likelihood of armed conflict occurring in a given grid cell (g) during time period (t) when drought conditions are absent ($W_{gt} = 0$). In this expression, (Y) denotes battle-death counts, (X) represents the set of control variables, and (W) is the drought indicator. Because the baseline risk is calculated with drought set to zero, it remains free from any contamination by interaction terms that involve both the underlying conflict risk and drought. This ensures an unbiased assessment of how the baseline conflict risk modifies the effect of drought on conflict intensity [46].

Second, predicted conflict risk ($\Pr(Y_{gt} > 0)$) captures the overall probability of conflict including all relevant factors. This serves as the sole predictor Z_{gt} in the zero-inflation equation (equation (3)). Unlike baseline conflict risk, drought is included here to ensure the most complete estimate of conflict probability. This approach works effectively because various methods can accurately estimate the zero-inflation probability π_{gt}, as long as they produce reliable estimates [21, 22].

2.3. Variable selection

Analyzing drought–conflict relationships across different contexts requires examining how drought interacts with multiple contextual variables. This creates significant methodological challenges in the ZINB model, which must account for over 66 variables and their interactions with drought, resulting in more than 100 parameters to estimate for the count process alone. Such high dimensionality raises concerns about model overfitting [20, 47].

The analysis addresses this challenge by employing a data-driven variable selection process to reduce dimensionality in the negative binomial component (equation (2)). Because SPEI acts as an exogenous treatment, the selection process can focus on identifying variables that best predict conflict intensity, because this will improve the precision of the treatment effect estimates [48]. The process begins by identifying 5000 observations with the highest baseline conflict risk from the GRF model, with drought's effects excluded to avoid incorporating treatment effects in variable selection ($\Pr(Y_{it} > 0|X_{it}, W_{it} = 0)$). The next step applies a boosted Tweedie regression, a form of machine learning, to a Yeo–Johnson transformed version of conflict intensity ($\lambda = 0.4$), creating a predictive model of conflict intensity [49]. The Tweedie regression serves a purely predictive purpose. It identifies which variables best explain conflict patterns rather than establishing causal relationships.

Out-of-sample permutation importance scores are then calculated for each variable by randomly shuffling its values and measuring the resulting decline in the model's predictive accuracy. A larger decline in accuracy indicates that the variable contributes unique information for predicting conflict intensity-information that cannot be captured by other variables in the model. This approach helps address multicollinearity by identifying variables that provide distinct rather than overlapping predictive contributions [49]. For each model specification, the 10 variables with the highest importance scores serve as covariates in the negative binomial model. Across specifications, baseline conflict risk emerges as the strongest predictor of conflict intensity, followed by population, distance to the capital, and agricultural variables (see supplementary information 4). The specific variables selected differ across model specifications depending on their relative unique contributions to prediction.

2.4. Modeling conflict intensity: ZINB model

Battle death data has two key components: the occurrence of conflict (extensive margin) and the number of resulting deaths (intensive margin) [42]. While this analysis focuses specifically on how droughts affect conflict intensity, most observations show zero deaths, creating a pattern that standard statistical models cannot adequately handle. Failing to account for this abundance of zeros would bias estimates of drought's effects on conflict intensity. To address this challenge for analyzing intensity specifically, this study employs a ZINB model, which combines two components. The first component determines a location's underlying conflict incidence potential—distinguishing between regions where conflict rarely or never occurs and regions that experience periodic conflict risks. The second component then models how many deaths occur among those regions with periodic conflict risks (conflict intensity), accounting for the fact that conflict intensity can vary substantially even among regions experiencing violence [20–22]. By modeling both whether conflict can occur and how intense it might be, this approach prevents bias that can occur when conflict incidence affects estimates of conflict intensity.

The model can be expressed formally as:

$$Y_{gt} \sim \begin{cases} 0 & \text{with probability } \pi \\ \mathrm{NB}\left(\lambda_{gt}, \theta\right) & \text{with probability } (1-\pi), \end{cases} \tag{1}$$

The formulation deliberately keeps both spatial resolution (g) and temporal frequency (t) flexible to accommodate multiple model specifications. Using a ZINB model suitable only for count data (i.e. battle deaths), this formulation addresses two distinct mechanisms generating zero death counts: either because conflict is structurally impossible (with probability π), or because conflict is possible but did not result in deaths in that period (through the negative binomial distribution). The expected number of deaths, λ, follows the model:

$$\log\left(\lambda_{gt}\right) = \beta_0 + \beta_1 X_{g,t-1y} + \beta_2 W_{gt} + \beta_3 W_{gt} X_{g,t-1y} + \gamma_g + \delta_y. \tag{2}$$

The probability of excess zeros (π) in equation (1) is estimated using a logit function, which models the probability that an observation has a structural zero (guaranteed absence of conflict):

$$\mathrm{logit}\left(\pi_{gt}\right) = \ln\left(\frac{\pi_{gt}}{1-\pi_{gt}}\right) = \alpha_0 + \alpha_1 Z_{gt}. \tag{3}$$

The model includes random effects that account for unobserved factors specific to each grid cell (γ) and year (δ). Z represents predictors for the zero-inflation component, while the parameter θ accounts for over-dispersion in death counts. The key parameter of interest, β_3, captures how drought's effects on conflict vary across different contexts. A likelihood ratio test where the null hypothesis is $\beta_3 = 0$ determines whether these effects are significantly heterogeneous (see section 3.1). If β_3 differs significantly from zero, this provides evidence that drought's impact

on conflict varies systematically with local conditions rather than being uniform across all contexts.

The analysis uses several strategies to ensure reliable results. First, to avoid bias from using variables that might be affected by drought itself (known as the 'bad control' problem) [46, 50], all control variables are measured one year before the drought period. This approach works because current droughts cannot influence conditions from the previous year. Second, the drought measure (SPEI) provides a reliable way to identify drought effects since it is based purely on climate data rather than social or economic factors that could be influenced by conflict. This makes SPEI a commonly used tool in conflict research [9, 11, 41–43]. However, climate change may cause drought patterns to shift differently across regions over time in ways that relate to conflict risk factors [36], which the analysis accounts for through additional controls.

To address potential bias from unobserved factors, the analysis employs random effects at the year and grid cell levels (δ_y and γ_g). This approach follows the same logic as traditional fixed-effects models for controlling unobserved omitted variable bias, but uses a more efficient estimation strategy. Rather than including a separate dummy variable to estimate each grid cell and year-specific effect, which would require thousands of parameters, the random effects model makes the distributional assumption that these effects are drawn from a Gaussian distribution with mean zero and estimated variance parameters. This allows the model to estimate the same location- and time-specific effects that capture unobserved characteristics such as local governance quality, cultural factors, or economic conditions, but with far fewer parameters while remaining computationally efficient. This estimation approach is implemented using the glmmTMB package in R [51].

Additionally, controlling for baseline conflict risk addresses potential omitted variable bias that could shape drought–conflict relationships. Climate change may cause drought probability to shift differently across grid-cells over time in ways that correlate with conflict risk factors, requiring statistical adjustments. The baseline conflict risk control helps mitigate this potential bias by accounting for these spatially differentiated patterns.

2.4.1. Bootstrapping standard errors

Conflict intensity data exhibits both spatial and temporal autocorrelation [52], which must be addressed when calculating standard errors to avoid underestimating parameter variance and ensure valid causal inference. Bootstrapping offers a method to calculate robust standard errors through resampling that can address these spatial and temporal autocorrelation challenges. The procedure works by repeatedly drawing samples from the original data, re-estimating the model on each sample, and using the variation in parameter estimates across samples to calculate standard errors [53].

To preserve the spatial and temporal correlation structure in the data, this analysis uses moving blocks bootstrapping [54]. The method creates 200 bootstrap samples with replacement, each containing up to 100 000 total data points from the original dataset. For each bootstrap sample, anchor points (specific grid cells and years) are randomly selected. Around each anchor point, all observations from that grid cell and surrounding cells across three consecutive years (the anchor year plus 1 year before and after) are included. This process repeats until the sample reaches its target size. The standard deviation of parameter estimates across all bootstrap samples provides the standard errors for causal inference. This sampling approach maintains the spatial and temporal clustering that characterizes the original data.

2.4.2. ZINB convergence

Some specifications cannot be analyzed because the ZINB models fail to converge. ZINB models face two distinct convergence problems. First, some specifications have too few conflict observations to run the analysis. Second, among the remaining specifications, models sometimes fail to converge because there is insufficient variation in conflict events. Figures 4 and 5 show the number of valid specifications used to generate each result.

2.5. Modeling conflict incidence: causal forest

While the ZINB model effectively captures conflict intensity dynamics, it has important limitations for analyzing heterogeneity in conflict incidence. The model combines zero outcomes from both the negative binomial and zero-inflation components, making it difficult to isolate conflict incidence parameters. Additionally, while the logit structure of the zero-inflation component works well for modeling conflict incidence in general, it cannot effectively accommodate the large number of parameters needed to identify the heterogeneous causal effects of drought on conflict intensity.

To address these limitations, the analysis uses a causal forest methodology implemented through the GRF package in R. This approach, which extends traditional random forest machine learning techniques, is specifically designed to detect heterogeneous treatment effects. The method estimates treatment effects $\tau(X_{gt})$ by calculating the difference in expected outcomes between treated and untreated conditions:

$$\tau\left(X_{gt}\right) = E\left[Y_{gt}|X_{gt}, W_{gt} = 1\right] - E\left[Y_{gt}|X_{gt}, W_{gt} = 0\right]. \quad (4)$$

The GRF package includes a calibration test that explicitly evaluates the presence of treatment effect heterogeneity. The test works by regressing the estimated treatment effects on other X variables and testing whether these characteristics jointly predict variation in drought's impact. Under the null hypothesis, drought effects remain constant regardless of local conditions. Rejection of this hypothesis provides statistical evidence that drought's impact on conflict occurrence varies meaningfully across different contexts. This testing framework offers more robust analysis of treatment effect heterogeneity in conflict incidence compared to the ZINB model's limitations in this context [19, 55].

Like the conflict intensity analysis, the conflict incidence analysis must address potential omitted variable bias from spatially heterogeneous changes in drought risk due to climate change [36]. The causal forest model addresses omitted variable bias through the GRF's causal forest algorithm [56] (see section 2.5). This methodology first calculates expected values for both drought ($E[W_{gt}|X_{gt}]$) and conflict ($E[Y_{gt}|X_{gt}]$) using all available predictors. It then examines only the unexpected variations—specifically, how deviations from predicted drought patterns ($W_{gt} - E[W_{gt}|X_{gt}]$) relate to deviations from predicted conflict patterns ($Y_{gt} - E[Y_{gt}|X_{gt}]$). By focusing on these unexplained variations rather than raw values, the approach minimizes the risk that measurement errors in SPEI data systematically correlate with conflict predictors, thus providing more reliable estimates of drought's causal effects on conflict incidence.

3. Results

3.1. Testing for heterogeneity

The analysis begins by examining whether the relationship between droughts and conflict is heterogeneous, addressing each component of conflict-incidence and intensity-separately. For conflict incidence, the study employs a calibration test using the GRF package (section 2.5). This calibration test directly evaluates whether drought's effects on conflict incidence are heterogeneous [19, 55, 58].

Figure 2 plots the cumulative distribution function of p-values from the calibration tests for heterogeneity conducted across specifications. Each line represents tests where one specification aspect is held constant (e.g. all tests using 1 month temporal resolution) while systematically varying all other specification choices, allowing examination of whether heterogeneity patterns differ by specification type. Under the null hypothesis of homogeneous treatment effects, these p-values would follow a 45° line. Each p-value represents the probability of the observed data occurring if drought affects conflict incidence homogeneously [19, 55]. The observed distribution shows modest deviation above this line, with approximately 25% of specifications reaching statistical significance at the 10% level. This pattern suggests that drought's causal effects on conflict incidence are heterogeneous.

The analysis then examines heterogeneous effects of drought on conflict intensity by testing the joint significance of interaction terms between drought shocks and key conflict predictors identified in section 2.3. This approach employs likelihood ratio tests comparing two ZINB models: one including interaction terms between drought and covariates ($X_{it} * W_{it}$), and another without these interactions [21, 22, 59]. If the model with interaction terms significantly outperforms the simpler model, this indicates that drought's effects on conflict intensity are heterogeneous [20].

Figure 3 shows the cumulative distribution of p-values from likelihood ratio tests that examine the joint significance of interaction terms across specifications, with random effects controls at the grid-cell and annual levels. Under the null hypothesis that drought effects on conflict intensity are homogeneous (meaning interaction terms are not jointly significant), these p-values would follow a 45° line. Instead, the interaction terms achieve statistical significance at 10% level in nearly all cases. This provides strong evidence that drought's effects on conflict intensity are heterogeneous.

These findings hold broadly across regions, temporal resolutions, spatial resolutions, and conflict types. North America is the only exception to this trend. However, this is likely because only eight specifications had enough non-zero observations to conduct the analysis. The results remain robust to alternative model specifications (see supplementary information section 3). Together, these analyses reveal modest evidence of heterogeneity in how drought affects conflict incidence, but substantial evidence of heterogeneity in its effects on conflict intensity.

3.2. Main sources of heterogeneity

Having established that droughts affect conflict intensity heterogeneously, the analysis turns to the second research question: *what are the main sources of this heterogeneity?* Given the stronger evidence for heterogeneous effects on conflict intensity compared to conflict incidence, subsequent analysis focuses exclusively on understanding the factors that shape drought's impact on conflict intensity. The ZINB model enables estimation of how different factors influence these effects. Figure 4 quantifies the importance of different variables by showing how often each drought interaction term was both selected by the variable selection procedure (section 2.3) and achieved statistical significance at the 10% level.

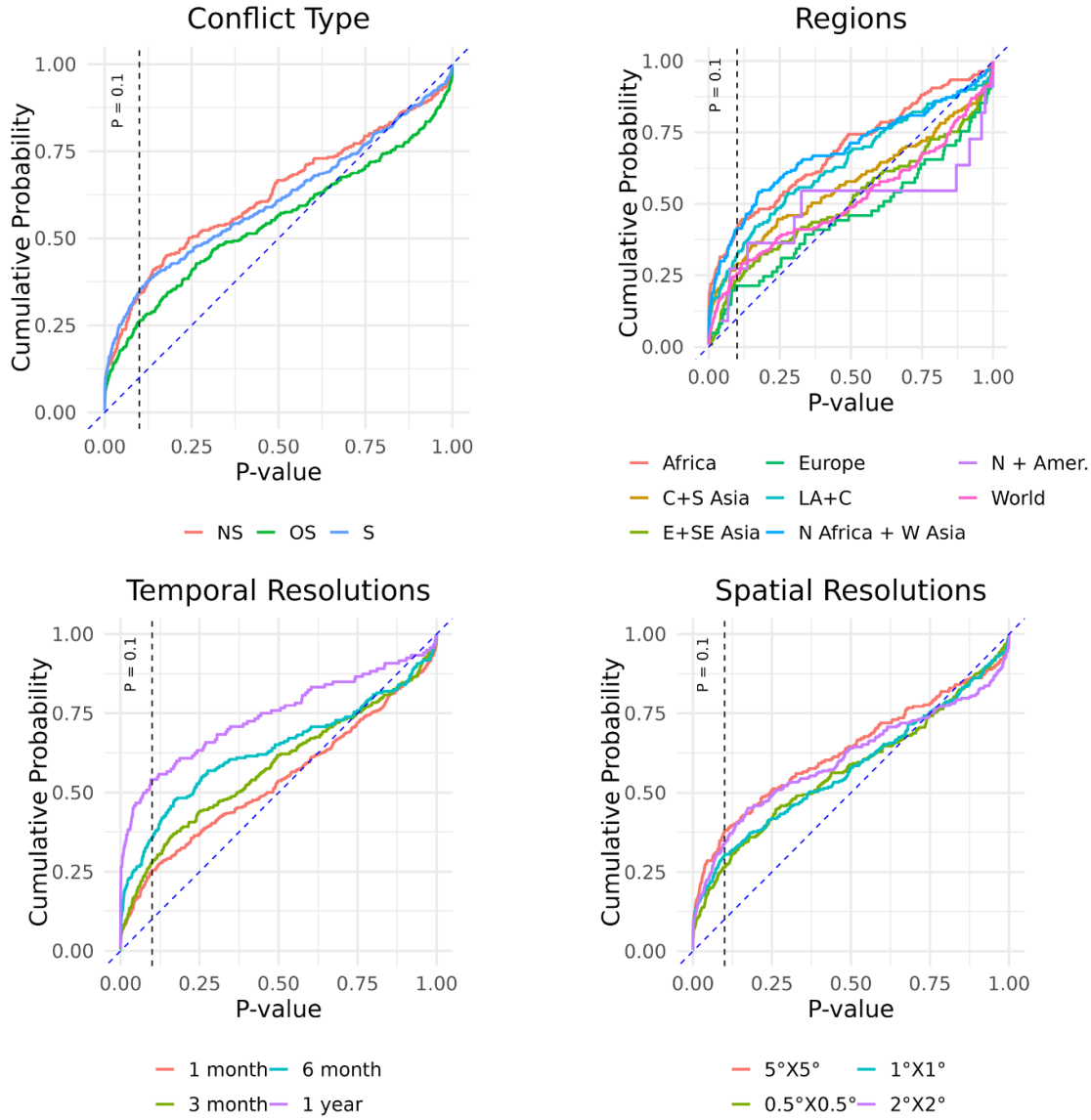

Figure 2. Cumulative distribution of *p*-values testing for effect heterogeneity in drought–conflict incidence relationships. This figure shows the cumulative distribution of *p*-values from calibration tests examining heterogeneity in how droughts affect conflict incidence across different dimensions [57]. The panels display results across conflict types (top left), geographical regions (top right), temporal resolutions (bottom left), and spatial resolutions (bottom right). The dashed 45° line represents the theoretical distribution under the null hypothesis of homogeneous effects. The empirical distributions generally lie above this line suggesting some heterogeneity. However, the relatively modest deviations from the 45° line indicate much less evidence of heterogeneity than is found for conflict intensity (see figure 3). In each panel, the vertical dashed line marks the conventional 10% significance threshold. For conflict types, NS denotes non-state conflicts, OS represents one-sided violence, and S indicates state-based conflicts.

Figure 4(a) reveals baseline conflict risk as the dominant source of heterogeneity in drought–conflict relationships. The interaction between baseline conflict risk and drought achieves statistical significance at the 10% level in 17.7% of specifications, substantially higher than any other variable. No other factor shows significant interaction with drought in more than 10% of specifications, though some models could not be estimated due to insufficient conflict cases. These results indicate that baseline conflict risk is the most important source of heterogeneity in the drought–conflict intensity relationship, and the only factor that is important across a broad set of specifications.

The baseline conflict risk variable aggregates information from multiple covariates to estimate out-of-sample conflict probability without a drought (see section 2.2). This composite nature raises the possibility that it may mask other important sources of heterogeneity. Variables that appear significant only when baseline conflict risk is excluded from the analysis likely influence drought–conflict relationships indirectly through their effect on baseline conflict risk. To test this possibility, the analysis was repeated without including baseline conflict risk as an interaction term.

When baseline conflict risk is excluded from the analysis, figure 4(b) shows population achieves

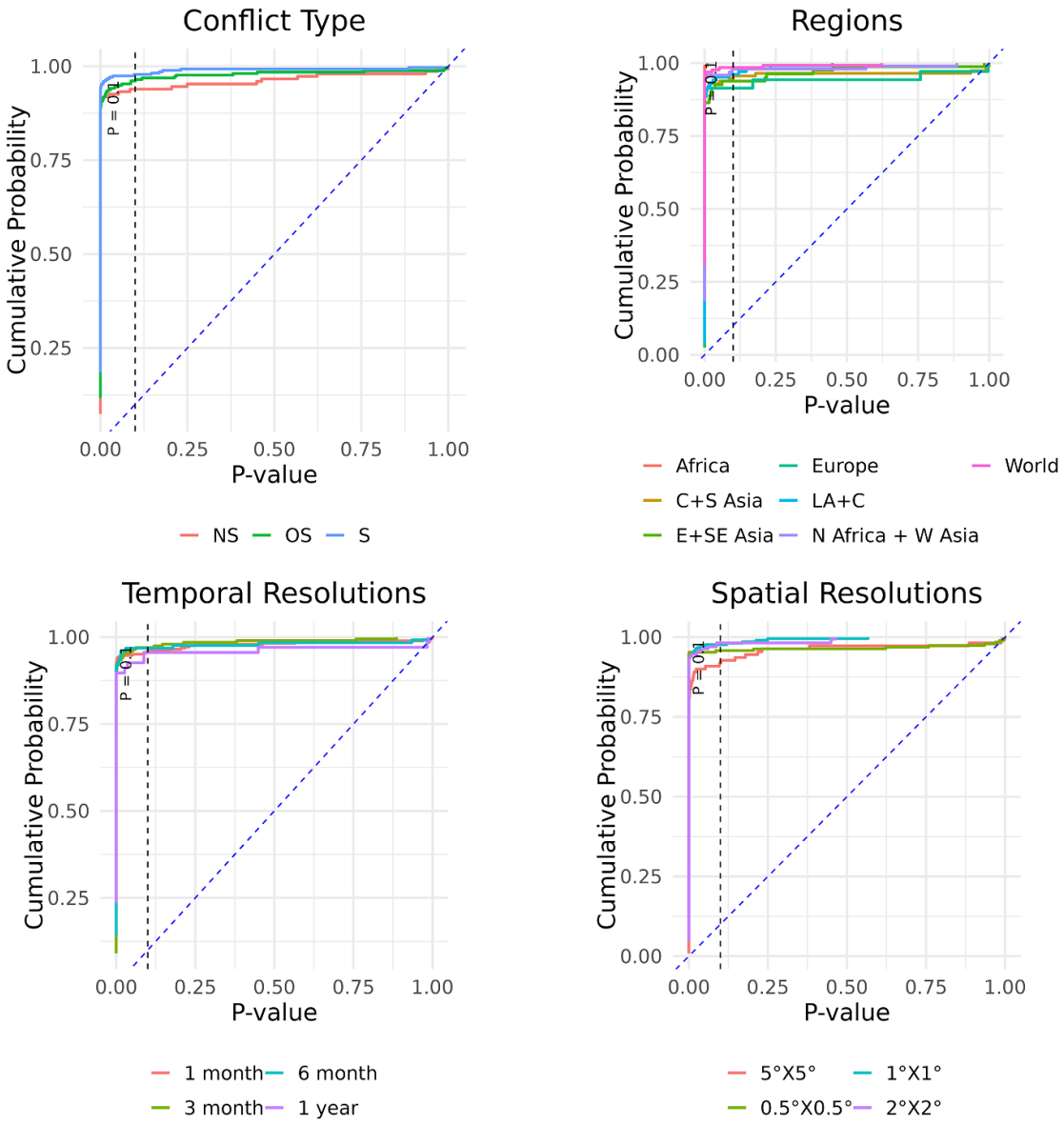

Figure 3. Cumulative distribution of *p*-values testing for effect heterogeneity in drought–conflict intensity relationships. This figure shows the cumulative distribution of *p*-values from likelihood ratio tests specifically examining the joint significance of interaction terms between drought and the top 10 conflict predictors. The panels display results across conflict types (top left), geographical regions (top right), temporal resolutions (bottom left), and spatial resolutions (bottom right). The dashed 45° line represents the theoretical distribution under the null hypothesis of homogeneous effects. The substantial deviations above this line provide strong evidence for heterogeneous effects across all dimensions. In each panel, the vertical dashed line marks the conventional 10% significance threshold. All models include direct effects of droughts, baseline conflict risk, and both grid cell and yearly controls. For conflict types, NS denotes non-state conflicts, OS represents one-sided violence, and S indicates state-based conflicts.

statistical significant in 11.5% of cases and agricultural intensity and globalization achieve significant at the 11.6% and 14.2% of the time for non-state and OS violence respectively. This suggests these variables may influence drought–conflict relationships primarily through their contribution to baseline conflict risk. However, given that the analysis considers 66 variables, some of these relatively low significance rates could also reflect spurious correlations.

3.2.1. Testing for a threat-multiplier effect

Having identified baseline conflict risk as the main source of heterogeneity in drought–conflict relationships, the analysis examines whether droughts act as 'threat-multipliers' for conflict intensity. A threat-multiplier dynamic means that droughts do not independently create new conflict risks, but instead compound pre-existing vulnerabilities [60, 61]. This would manifest empirically as minimal drought effects on conflict intensity in stable regions,

	NS	OS	S	Total
Total	231	325	354	910
Drought*Baseline Conf. Risk	15.2%	19.7%	17.5%	17.7%
Drought*Population	6.5%	4.0%	4.2%	4.7%
Drought*Agricultural Employment	4.8%	6.2%	2.0%	4.2%
Drought*Agricultural Intensity	3.9%	4.3%	3.4%	3.8%
Drought*Urban Pop.	1.3%	4.6%	3.7%	3.4%
Drought*Globalization Ind.	4.3%	3.1%	2.8%	3.3%
Drought*Distance to Capital	4.8%	2.8%	2.8%	3.3%
Drought*Infant Mortality Rate	1.3%	4.6%	3.1%	3.2%
Drought*Average Air Temperature	2.6%	3.4%	3.4%	3.2%
Drought*Precipitation	4.3%	1.2%	3.4%	2.9%
Drought*Night Light Ind.	2.2%	4.0%	2.3%	2.9%
Drought*Pastures	3.9%	1.5%	3.1%	2.7%
Drought*Income Ind.	2.2%	2.8%	2.8%	2.6%
Drought*Rainfed Cropland	3.0%	2.8%	1.7%	2.4%

(a) Analysis Including Baseline Conflict Risk

	NS	OS	S	Total
Total	233	325	354	912
Drought*Population	9.4%	13.2%	11.3%	11.5%
Drought*Globalization Ind.	6.0%	14.2%	4.5%	8.3%
Drought*Distance to Capital	6.0%	5.5%	9.9%	7.3%
Drought*Infant Mortality Rate	4.3%	5.5%	9.9%	6.9%
Drought*Agricultural Intensity	11.6%	3.7%	5.9%	6.6%
Drought*Agricultural Employment	7.7%	8.0%	4.0%	6.4%
Drought*Urban Pop.	6.9%	8.3%	3.7%	6.1%
Drought*Pastures	5.6%	4.3%	7.3%	5.8%
Drought*Rice	2.6%	8.6%	5.1%	5.7%
Drought*Suicide Rate	3.0%	4.3%	7.3%	5.2%
Drought*Irrigation Sum	7.3%	3.4%	5.1%	5.0%
Drought*GDP per Capita (PPP)	3.9%	5.8%	3.7%	4.5%
Drought*Rainfed Cropland	5.6%	4.0%	4.0%	4.4%
Drought*Maize	3.0%	4.6%	4.8%	4.3%

(b) Analysis Excluding Baseline Conflict Risk

Figure 4. Most important sources of heterogeneity in drought–conflict relationships: comparative analysis with and without baseline conflict risk. This figure compares the relative importance of different sources of heterogeneity in drought–conflict relationships, showing the percentage of specifications where each interaction term ranks among the top 10 most important predictors and achieves statistical significance at the 10% level. Panel A (left) includes baseline conflict risk in the analysis, revealing it as the dominant source of heterogeneity-significant in 17.7% of specifications. Notably, baseline conflict risk is the only source of heterogeneity significant in more than 10% of specifications when included in the analysis. Other variables exhibit substantially weaker heterogeneous effects (typically $< 5\%$). This pattern holds across all conflict types. Panel B (right) excludes baseline conflict risk, showing that population (11.5%), globalization (14.2% for one-sided violence), and agricultural intensity (11.6% for non-state violence) emerge as significant drivers of heterogeneous effects. The total number of specifications analyzed is shown at the top of each panel: 910 and 912, respectively. If all specifications had a sufficient number of observations with conflict and the ZINB model converged, there would be 448 specifications for each outcome. For conflict types, NS denotes non-state conflicts, OS represents one-sided violence, and S indicates state-based conflicts.

with progressively larger impacts in areas that already face high conflict risks, thus suggesting droughts exacerbate pre-existing conflict vulnerabilities.

Figure 5 shows that drought and baseline conflict risk have a small but generally positive relationship across different model specifications. While most effects are close to zero, positive estimates consistently outnumber negative ones. Outside North America, the typical interaction effect indicates that each 1 percentage point increase in baseline conflict risk is associated with a 0.25% increase in drought-induced conflict intensity. This suggests a modest 'threat multiplier' effect whereby the effect of drought on conflict intensity are higher when the baseline conflict risk is higher.

3.3. Results: importance of heterogeneity

Having established the presence of heterogeneous effects and identified baseline conflict risk as the primary source of this heterogeneity, this analysis now turns to the third research question: *How important are these heterogeneous effects for understanding overall armed conflict dynamics?* This question can be approached through several complementary analyses of the relative importance of heterogeneous effects.

The first approach examines the performance of the interaction terms in predicting conflict intensity. Among all interaction terms tested, only the interaction between drought and baseline conflict risk improves a prediction model's ability to predict conflict intensity (see supplementary information 2). The absence of predictive improvement from other interaction terms provides strong evidence that these proposed sources of heterogeneity play minimal roles in shaping conflict intensity [62].

The second approach examines whether the heterogeneous effects of drought are consistent in their direction and size. Figure 5 reveals that the interaction effects between drought and baseline conflict risk are small and clustered near zero. Although these effects are more often positive than negative, the 25th percentile of estimates are negative. The small magnitude of these effects, combined with their inconsistent direction, provides additional evidence that drought's varying impacts across different contexts play only a minor role in explaining overall patterns of conflict intensity.

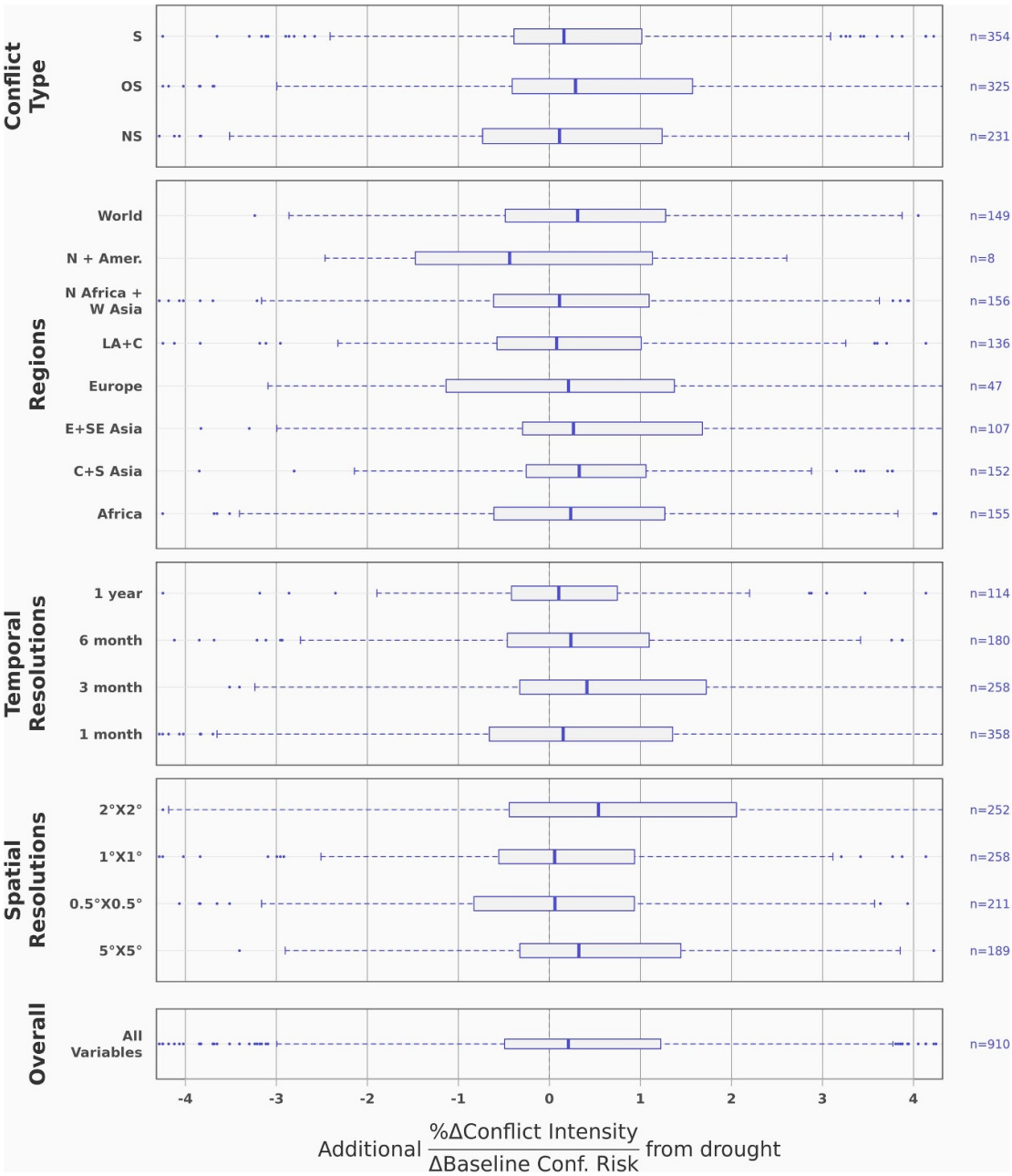

Figure 5. Distribution of drought*baseline conflict risk interaction effects across analysis dimensions. This figure illustrates the distribution of interaction effects between baseline conflict risk and drought on conflict intensity across different analytical dimensions. The analysis is disaggregated by conflict types, regions, and temporal/spatial resolutions. Each row displays results aggregated across all other dimensions (e.g. the one-sided violence (OS) row incorporates all combinations of temporal resolutions, spatial resolutions, and regions). The *x*-axis shows the percentage change in conflict intensity per percentage point increase in baseline conflict risk during drought conditions relative to non-drought conditions. While the overall distribution of effects tends to cluster around zero, positive effects are more common than negative effects. The overall median implies that a 1% point increase in baseline conflict risk is associated with a 0.25% increase in the causal impact of drought on armed conflict intensity. This pattern suggests modest threat-multiplier effects. For conflict types, NS denotes non-state conflicts, OS represents one-sided violence, and S indicates state-based conflicts.

4. Discussion

These findings contribute important insights to the broader climate-conflict literature. While previous research has emphasized that climate affects conflict primarily through indirect pathways that vary across contexts [6, 7, 10, 11, 14, 63], most attempts to synthesize these findings into a broader picture have relied either on literature reviews [23–27] or meta-analysis that average findings from different studies [37, 64, 65]. The systematic analysis presented here examines drought–conflict relationships across multiple temporal and spatial resolutions, conflict types, and regions, similar to recent work by Burke *et al* [37], while focusing specifically on heterogeneous effects. This comprehensive approach reveals that

droughts have heterogeneous effects on both conflict incidence and intensity, with stronger evidence for heterogeneity in conflict intensity. These effects on conflict intensity are primarily moderated by baseline conflict risk rather than other socioeconomic, political, or demographic factors. The analysis further demonstrates that drought's heterogeneous impacts play a relatively minor role in overall conflict dynamics. These findings suggest that the commonly emphasized context-dependency of climate-conflict relationships may be less pronounced than previously thought, at least regarding drought impacts.

Understanding how drought affects conflict requires distinguishing between two sets of mechanisms. The first is the 'threat-multiplier' effect, where drought's impact on conflict exacerbates pre-existing conflict risks [60, 61]—having little effect on conflict intensity in regions with low conflict risks but stronger consequences in areas with high conflict risks. Past research has identified several factors—including ethnic diversity [8], infant mortality rates [9], and population size [66]—that appear to modify how drought affects conflict. These same factors also contribute to baseline conflict risk. This creates a key analytical question: do these factors represent distinct pathways through which drought leads to conflict? Or do they influence drought–conflict relationships primarily through their contribution to baseline conflict risk? The answer has important implications for policy interventions.

The analysis demonstrates that baseline conflict risk is the most important factor explaining variation in drought-related conflict. This finding suggests that policies targeting general conflict prevention-addressing root causes like socio-economic development, conflict history, and ethnic grievances [67, 68]-may also effectively reduce climate-related security risks. While this conclusion cannot automatically extend to other climate impacts, it raises a crucial question: whether climate phenomena require distinct policy responses or can be addressed through existing conflict prevention strategies. The methodological framework presented here provides a template for systematically assessing how different climate impacts affect conflict.

Testing this framework across 66 socioeconomic, political, geographic, and environmental factors yielded surprising results that reinforce the main findings. Many commonly suggested mediating variables-including population, infant mortality, and democracy levels-initially appeared significant when tested individually but disappeared when tested across multiple model specifications. This suggests that previous findings highlighting specific sources of variation may be more specification-dependent than initially thought.

Finally, this paper finds that while drought effects on conflict are conditional and context-dependent, droughts still play only a small role in shaping conflict dynamics overall. This finding highlights a key gap in current climate-conflict research. The research consensus emphasizes that climate can influence armed conflict, but only under certain specific conditions [6], with different types of climate impacts affecting conflict in different ways across different contexts [14]. However, simply acknowledging that the climate-conflict relationship is 'complex' [63] may not prevent misleading narratives about how climate change drives violence [29]. The results presented here suggest that scholars need to move beyond only identifying when climate impacts might increase conflict risks. Even after accounting for heterogeneous effects across different contexts, researchers must also assess the overall magnitude of climate hazards' contribution to armed conflict dynamics.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://zenodo.org/records/17 204 025 [69].

Conflict of interest

The author has no competing interests to declare.

Author contribution

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Conceptualization (equal), Data curation (equal), Formal analysis (equal), Investigation (equal), Methodology (equal)

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