Forced to Flee: Climate change and conflict the Numbers Behind Conflict and Disaster Displacements in 2022*

Analyzing the Scale and Scope of Conflict Versus Natural Disasters and their impact on teh number of people displaced between 2008 and 2022

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April 17, 2024

Communities worldwide are increasingly forced to adapt to the devastating impacts of climate change, including droughts, floods, and rising sea levels. This study analyzes global displacement data from the Internal Displacement Monitoring Centre (IDMC) from 2008 to 2022. Findings reveal that displacements triggered by climate disasters have not only intensified but have also begun to surpass displacements driven by conflicts, signaling a significant shift in the causes of global migration patterns

1 Introduction

You can and should cross-reference sections and sub-sections. We use R Core Team (2023) and Wickham et al. (2019).

The remainder of this paper is structured as follows. Section 2….

Abstract

Here we draw from experiences of migrants, migrant aid workers and immigration lawyers to explore the dynamics of climate-driven migration and laying out a framework of how we think about climate challenges in migration in the context of HCI researchers. Background

In the face of sudden disasters and intense weather events, such as hurricanes and flash floods, to the more insidious progressions of environmental degradation, including gradual soil erosion and water scarcity, climate change is steadily uprooting communities and testing the bounds

*Code and data are available at: https://github.com/RayanAlim/Climate-migration of their resilience (Adger et al., 2009). For many, migration emerges as an essential response, occurring against a backdrop of escalating climate challenges. The Institute for Economics & Peace predicts that climate change could displace 1.2 billion people by 2050 (Institute for Economics & Peace, 2023).

Climate-Driven Migration

Climate change migration refers to the movement of people induced by climate change impacts such as extreme weather events, rising sea levels, and prolonged droughts (Black, 2011). This type of migration can be temporary or permanent, often occurring both within countries and across borders. The complexity of defining and quantifying such migration stems from the myriad ways in which climate impacts drive people from their homes, compelling them to seek safer or more viable living conditions.

The importance of addressing climate migration lies in its significant implications for global stability, human rights, and social equity. As climate change exacerbates existing vulnerabilities, particularly in less developed regions, it challenges the capacity of communities and nations to sustain their populations. Effective management and support of climate-induced migration are crucial in preventing humanitarian crises and conflicts that may arise from resource scarcity and population displaceme Climate Refugees

As the world is witnesses a surge in climate-induced migration, the term "climate refugees" is increasingly being used to refer to people who have been forced to leave their homes as a result of the effects of climate change on their environment (Jakobeit et al., 2016). However, the term lacks not have a legal definition nor are climate refugees an official status protected under international laws or the 1951 Refugee Convention which covers people fleeing population on the grounds of their race, religion, nationality,membership of a particular social group or political opinion (Betts, 2013).

Defining and quantifying climate migration is challenging because the factors driving displacement are often interwoven with socioeconomic and political pressures (Piguet et al., 2010). Livelihoods may be disrupted by a combination of environmental factors, such as declining crop yields due to drought and saltwater intrusion from rising sea levels, coupled with limited social safety nets and political instability (Warner, 2010). Enviromentalists themselves argue against a monolithic definition of "climate migration," highlighting the importance of distinguishing between environmental displacement triggered by sudden-onset events like hurricanes and the more gradual processes associated with environmental degradation (Castles, 2015).

2 Data

2.1 Data Sources

The primary dataset used in this study consists of data from the Internal Displacement Monitoring Centre (IDMC). The IDMC collects global data on internally displaced persons (IDPs) due to conflict, violence, and disasters. This data includes metrics on both the incidence of new displacements and the existing stock of displaced persons as of the end of each year.

2.2 Collection Methods

Data collection by IDMC involves a combination of direct data submissions, partnerships with local and international organizations, and comprehensive reviews of public reports and news articles. The collected data encompasses various events leading to displacement, documented systematically through an event-based monitoring approach. This method ensures that each displacement event is categorized and analyzed based on the location, date, trigger, and duration of displacement.

2.3 Variables in the Dataset

The key variables included in the dataset are:Country: The country where the displacement occurred.Year: The year of the data record.Type of Displacement: Categorized as conflict-induced or disaster-induced.New Displacements: The number of new displacements occurring within the reporting year.Stock of Displacement: The cumulative number of displaced individuals still displaced by the end of the reporting year.Causes of Displacement: Specific causes or events leading to displacement, such as armed conflict, violence, floods, earthquakes, etc.

2.4 Data Features

The dataset features comprehensive details on the scale and specifics of displacement:Geospatial Data: Information on the locations affected by displacement. - Disaggregated Data: Whenever available, data includes disaggregation by age, sex, and occasionally by disability status, offering insights into the demographics of displaced populations.

2.5 Sampling

Data by IDMC is not sampled but aggregated from comprehensive event-based monitoring and reporting from various sources, aiming to cover all incidences of internal displacement globally. Where data is not available directly, IDMC employs modeling techniques to estimate displacement figures.

2.6 Bias and Limitations

Several potential biases and limitations affect the data: - Reporting Bias: Displacement events are sometimes under-reported, especially in regions with limited access or media coverage. - Access Constraints: Conflict and violence may restrict access to certain areas, limiting data collection capabilities. - Data Overlap and Gaps: There may be overlaps or gaps in data due to the varied nature of sources and the challenge of integrating data from different reporting periods and methodologies. - Temporal and Geographical Coverage Variations: The frequency and detail of reporting can vary significantly across different regions and times.

The analysis was carried out using the statistical programming language `R` (R Core Team 2023), using the `tidyverse`(**citetidy?**), `here`(**citehere?**), and `readxl`(**citexl?**) packages. The figures and tables in the paper are generated using the, respectively, `ggplot2`(**citegg?**) and `knitr`(**citeknitr?**) packages.

3 Model

The goal of our modelling strategy is twofold. Firstly,…

Here we briefly describe the Bayesian analysis model used to investigate… Background details and diagnostics are included in Appendix B.

3.1 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$
\begin{aligned}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) && (1)\\
\mu_i &= \alpha + \beta_i + \gamma_i && (2)\\
\alpha &\sim \text{Normal}(0, 2.5) && (3)\\
\beta &\sim \text{Normal}(0, 2.5) && (4)\\
\gamma &\sim \text{Normal}(0, 2.5) && (5)\\
\sigma &\sim \text{Exponential}(1) && (6)
\end{aligned}
$$

We run the model in R (R Core Team 2023) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`.

Table 1: Explanatory models of flight time based on wing width and wing length

	First model
(Intercept)	1.12
	(1.70)
length	0.01
	(0.01)
width	−0.01
	(0.02)
Num.Obs.	19
R2	0.320
R2 Adj.	0.019
Log.Lik.	−18.128
ELPD	−21.6
ELPD s.e.	2.1
LOOIC	43.2
LOOIC s.e.	4.3
WAIC	42.7
RMSE	0.60

3.1.1 Model justification

We expect a positive relationship between the size of the wings and time spent aloft. In particular…

We can use maths by including latex between dollar signs, for instance θ.

4 Results

Our results are summarized in Table 1.

Talk more about it.

And also planes (Figure 2). (You can change the height and width, but don't worry about doing that until you have finished every other aspect of the paper - Quarto will try to make it look nice and the defaults usually work well once you have enough text.)

Talk way more about it.

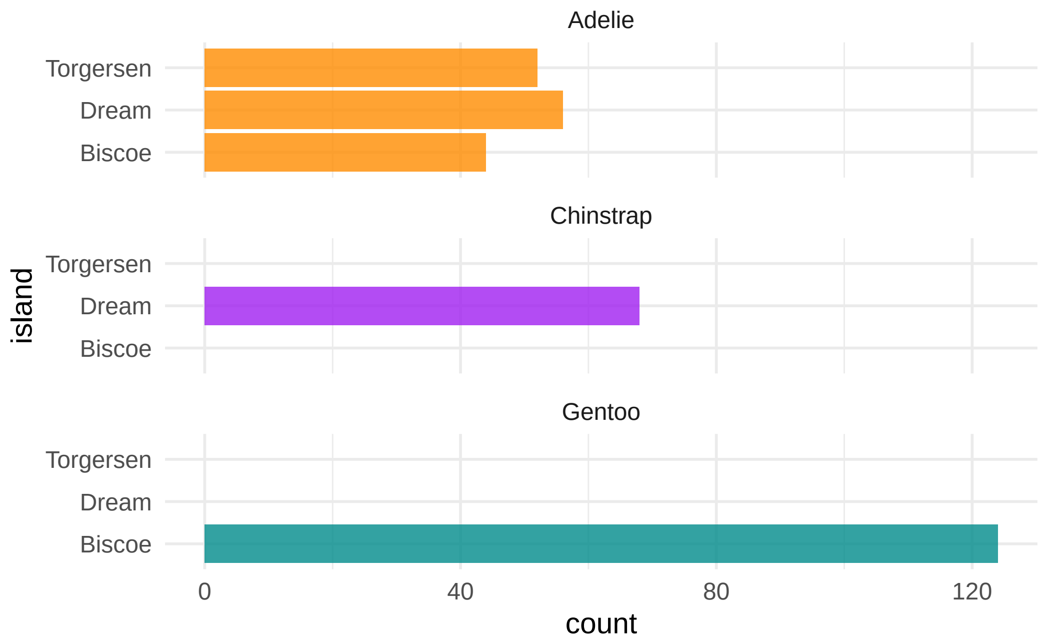


Figure 1: Bills of penguins

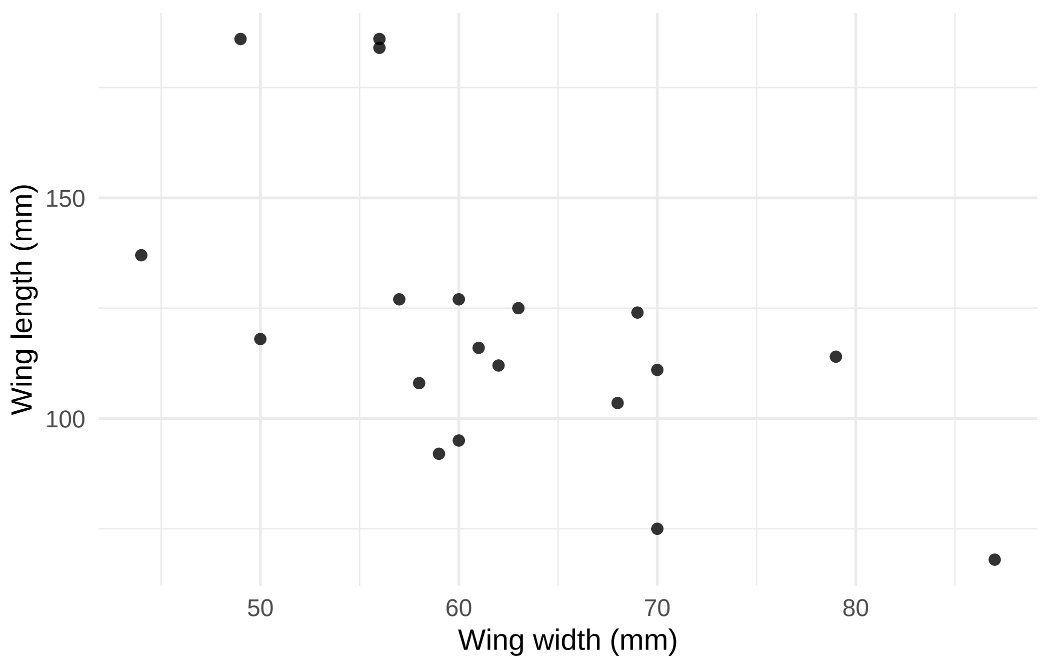


Figure 2: Relationship between wing length and width

5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

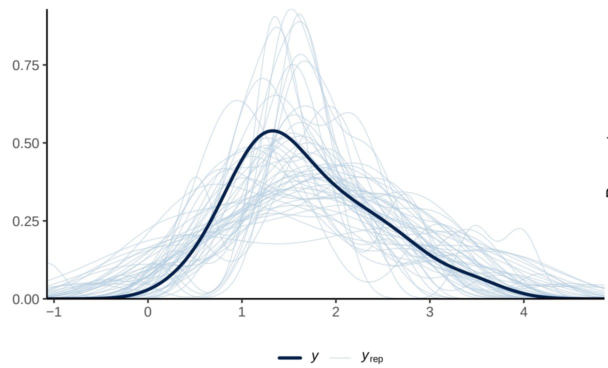
A Additional data details

B Model details

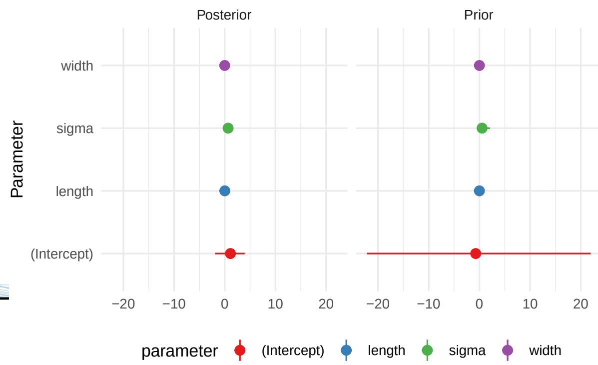
B.1 Posterior predictive check

In Figure 3a we implement a posterior predictive check. This shows...

In Figure 3b we compare the posterior with the prior. This shows...



(a) Posterior prediction check



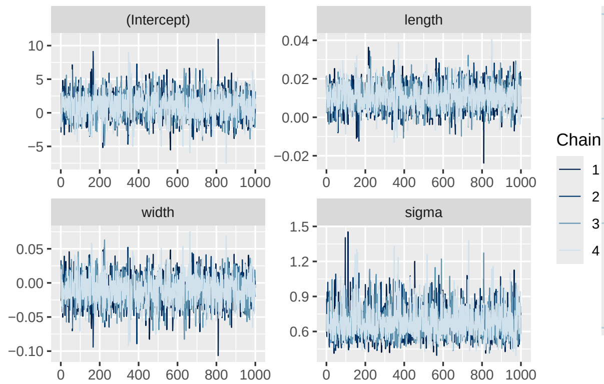
(b) Comparing the posterior with the prior

Figure 3: Examining how the model fits, and is affected by, the data

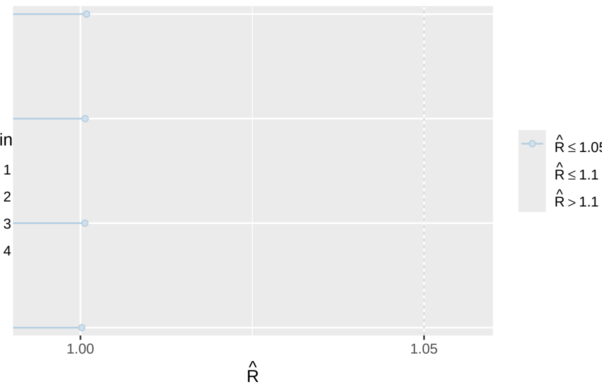
B.2 Diagnostics

Figure 4a is a trace plot. It shows... This suggests...

Figure 4b is a Rhat plot. It shows... This suggests...



(a) Trace plot



(b) Rhat plot

Figure 4: Checking the convergence of the MCMC algorithm

References

Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2022. "Rstanarm: Bayesian Applied Regression Modeling via Stan." https://mc-stan.org/rstanarm/.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.