Analyzing Toronto's Historical Climate Data with Global Warming Impacts"*

A study of Toronto's environmental data over the last thirty years

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This essay uses the Toronto Monthly Weather Normals Dataset to investigate the relationship between thirty years of weather data from Toronto and global warming trends. By analyzing long-term patterns in temperature, precipitation, and other climatic variables, the study identifies clear signals of climate change within the local context of Toronto. The findings underscore the broader implications of rising temperatures and changing weather patterns, linking local observations to global climate change phenomena and providing evidence for the urgent need for environmental policy and urban planning to adapt to these shifts.

1 Introduction

The global discourse on climate change is increasingly underscored by localized studies that trace the manifestation of global warming through decades of weather data. This paper centers on the Toronto Monthly Weather Normals Dataset, which encapsulates thirty years of detailed meteorological data, to explore the nuances of climate change in Toronto. Through a comprehensive analysis of this dataset, the research seeks to draw correlations between the observed long-term weather trends in Toronto and the broader global warming patterns. The study delves into the intricacies of temperature fluctuations, precipitation changes, and other climatic variations, providing a nuanced understanding of how global climate dynamics are reflected in Toronto's local environment. This analysis contributes to the scientific understanding of climate change. It informs policy development and urban planning strategies, emphasizing the critical role of localized climate data in addressing the global challenge of climate change.

*Code and data are available at: https://github.com/QPP123/Toronto-Historical-Data-With-Global-Warming-Public

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....

2 Data

Some of our data is of penguins (Figure 1), from Horst, Hill, and Gorman (2020).

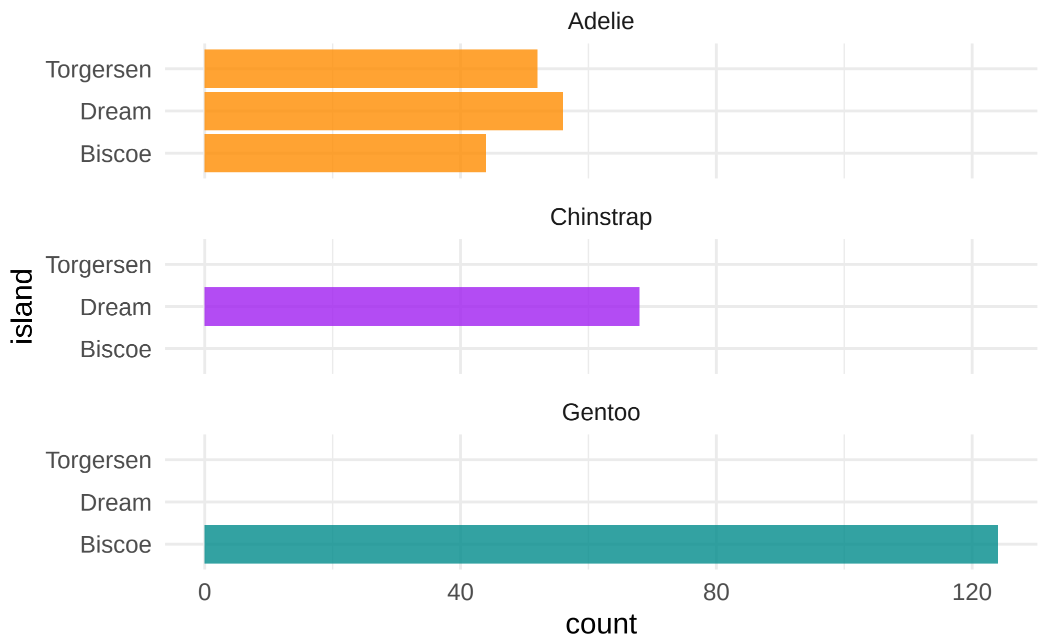


Figure 1: Bills of penguins

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.

3 Model

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

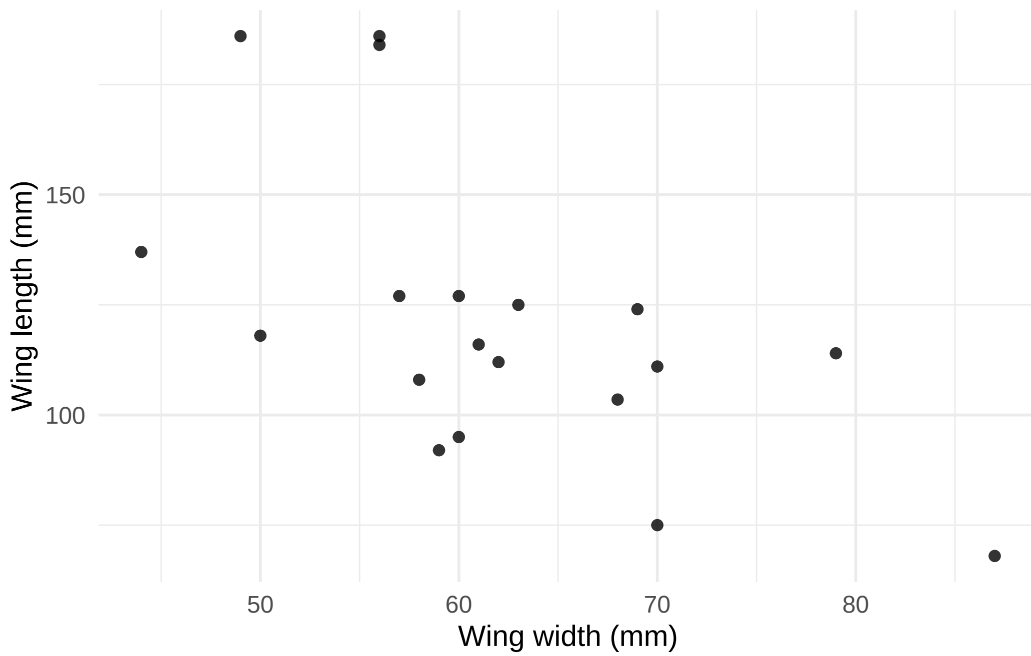


Figure 2: Relationship between wing length and width

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.

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

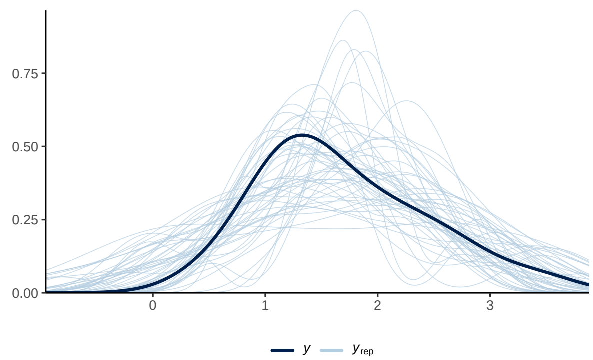
A Additional data details

B Model details

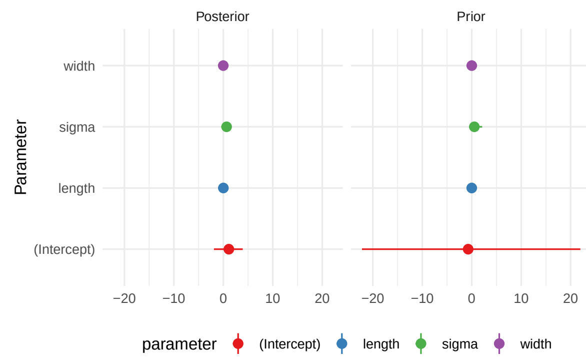
B.1 Posterior predictive check

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



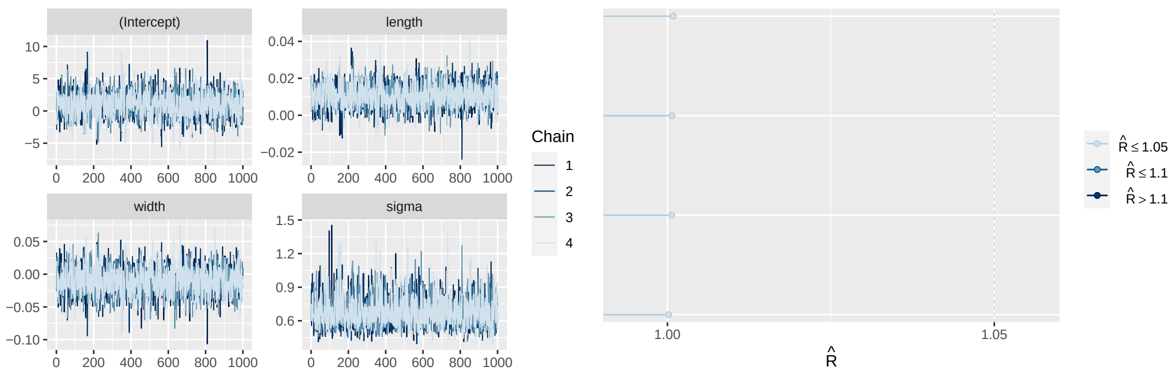
(b) Comparing the posterior with the prior

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/.

Horst, Allison Marie, Alison Presmanes Hill, and Kristen B Gorman. 2020. *Palmerpenguins: Palmer Archipelago (Antarctica) Penguin Data*. https://doi.org/10.5281/zenodo.3960218.

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.