Modeling Annual Atlantic Major Hurricanes Using Binomial Regression

A report for Princeton CEE 599

Emma Levin (el2358@princeton.edu)
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Abstract

Annual Atlantic major hurricane (MH) frequencies are modeled using large-scale environmental predictors, including thermodynamic variables (hurricane potential intensity and moist entropy deficit) and dynamic variables (vertical wind shear and vorticity). The fraction of North Atlantic tropical cyclones that intensify into MHs is analyzed using a binomial regression model, with model selection conducted via a forward selection approach based on the Akaike Information Criterion (AIC). The data are derived from a 10-member ensemble of an atmosphere-only climate model forced by historical sea surface temperatures. Results indicate that thermodynamic variables primarily govern the intensification fractions.

1 Introduction

Major North Atlantic hurricanes (MH; Saffir-Simpson Scale categories 3, 4, and 5 with winds exceeding 111 mph) are the deadliest, costliest storms to coastal communities in the United States and Caribbean (Emanuel (2010)). Thus, understanding the physical mechanisms governing the transition of a category 1 or 2 hurricane to a MH is highly relevant for damage mitigation efforts.

Several studies (Hsieh et al. (2020), Hsieh et al. (2022), Hsieh et al. (2023), Yang et al. (2021)) developed a theoretical framework to understand the physical processes governing the two primary steps of hurricane (tropical cyclone; TC) development. Their ansatz is

$$n_{TC} = n_s \times P, \tag{1}$$

where n_{TC} and n_s are the frequency of TCs and the frequency of weakly rotating seeds that may develop into a TC. P represents the probability that a given rotating TC precursor transitions into a TC. This framework suggests that TC formation can be understood probabilistically: all TCs originate from seeds, but the transition of a specific seed into a TC involves inherent randomness (Vecchi et al. (2019)).

These aforementioned studies suggest that different large-scale environmental conditions govern n_s and P. For example, the authors developed a parametrization of n_s that is a function of several different large-scale environmental conditions such that

$$n_s \approx -\omega \frac{1}{1 + Z^{-1/\alpha}}, \tag{2}$$

where ω is monthly mean vertical velocity at 500 hPa, Z is a function of monthly mean relative vorticity, and α is a fitted constant. Similarly, Hsieh et al. (2020) posits the following proxy for P, which is also a function of different environmental variables:

$$P \approx \frac{1}{1 + (\Lambda_0/\Lambda)^{-1/\gamma}}, \tag{3}$$

where Λ_0 and σ' are constant fitting parameters, and Λ is the ventilation index defined by Chavas (2017), Tang and Emanuel (2010), and Tang and Emanuel (2012), which measures the degree to which the influx and circulation of cold dry air into the storm's convective plume can inhibit the storm's strength. The ventilation index is a non-dimensional metric:

$$\Lambda = \frac{\nu_s \cdot \chi}{PI}, \tag{4}$$

where ν_s is the vertical wind shear (the magnitude of wind differences between the lower and upper troposphere), PI is potential intensity (measure of maximum strength of a storm that is highly correlated with SSTs; Emanuel (1986a) and Emanuel (1986b)), and $\chi = (s_b - s_m)/(s_0^* - s_b)$ is a dimensionless parameter representing the moist entropy deficit in the middle troposphere, which increases as the middle troposphere becomes drier (Emanuel (2010)). s_b, s_m, and s_0^* are the moist entropies of the boundary layer and middle troposphere, and the saturation moist entropy of the sea surface, respectively.

Here, we seek to extend Hsieh et al. (2020)'s ansatz to describe the number of North Atlantic MH such that

$$n_{MH} = n_{TC} \times P_{MH} = n_s \times P \times P_{MH}, \tag{5}$$

where P_{MH} is the probability that a TC transitions into a MH. Our goal is to model the relationship between and large-scale environmental variables. Several studies (e.g. Elsner and Jagger (2004), Villarini et al. (2010), and Villarini et al. (2012)) have explored similar dependencies, modeling TC frequencies, landfalling TC frequencies, and fractional landfalling TC frequencies in relation to large-scale environmental conditions and climate indices using Poisson and binomial regression approaches. While some studies have utilized Poisson regression to link environmental factors such as rainfall and winds (Elsner and Schmertmann (1993)) or climate indices like the North Atlantic Oscillation (Elsner et al. (2000)) to annual MH frequencies, to our knowledge, no research has examined how the relative fraction of TCs transitioning into MHs depends on large-scale environmental conditions.

From a statistical standpoint, the appropriate model to describe the proportion of hurricanes making landfall is a binomial model, in which the number of landfalling hurricanes has a binomial distribution given the total number of storms. Thus, following the methods of Villarini et al. (2012), we will model the relationship between P_{MH} and large-scale environmental variables using binomial regression to determine which covariates are the most important in predicting the transition from a TC to a MH. Doing so gets us closer to a parametrization for P_{MH} akin to the parametrizations for n_s and P outlined in equations 2 and 3.

In addition the functions outlined in equations 2 and 3 from Hsieh et al. (2020), other studies have developed indices that relate the large scale environment to TC frequency, (e.g., Bruyère et al. (2012); Emanuel and Nolan (2004); Emanuel (2010); Tippett et al. (2011); Wang and Murakami (2020)). These indices, known as genesis potential indices (GPIs), relate local environmental factors thermodynamic and dynamic factors— such as PI, wind shear, humidity, and χ—to TC activity. GPIs are typically calculated from monthly averages of model projections or observational data, representing regional climatology rather than instantaneous weather conditions (Sobel et al. (2021)). While no GPIs have been specifically developed to study MHs, we incorporate several variables from existing GPIs as potential covariates in our regression model.

We construct a Binomial regression for multiple covariates using a 10-ensemble member historical simulation of a state-of-the-art atmosphere-only climate model.

In this study we address the following questions:

1. Can the fractional data for the North Atlantic basin MHs be modeled by a Binomial distribution?

2. Which covariates are significant in modeling the fractional MH data?

In Section 2 we describe the climate model from which we generate the MH and covariate date. In Section 3 we provide a description of Binomial statistical model used to describe MH counts. In Section 4 we discuss the results of study, and in Section 5 we highlight the implications of our results.

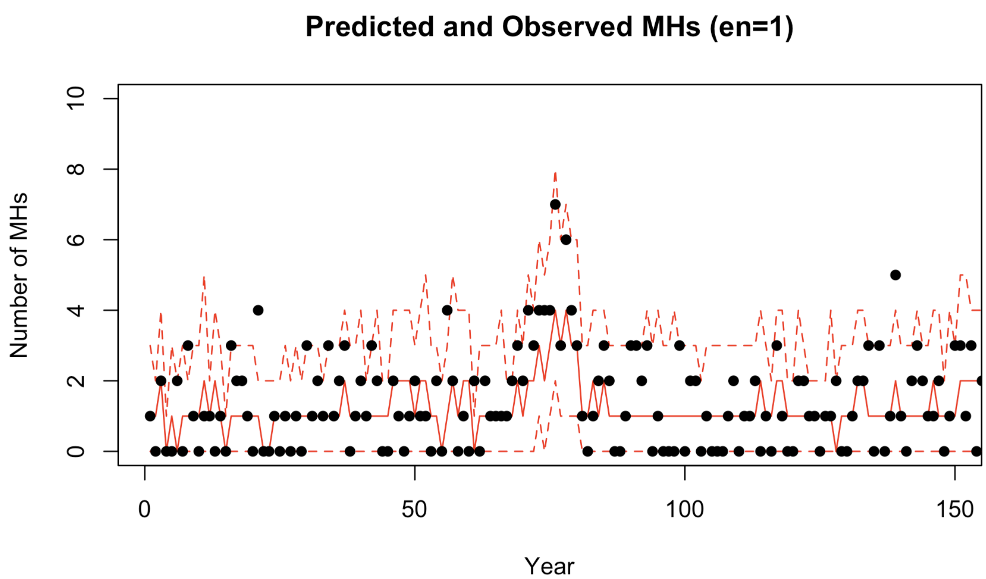

Figure 1: Prediction of yearly MH frequencies values using the fitted Binomial regression model (red lines) for the first ensemble member of the AM2.5-C360 model simulation. The dotted red lines represent the 5th and 95th percentiles of the predicted values, while the black dots indicate the observed values.

2 Data

Historical MH frequencies were derived using the Geophysical Fluid Dynamics Laboratory (GFDL) Atmospheric Model version 2.5 with C360 resolution (AM2.5-C360). This model, part of the atmospheric component of the GFDL Climate Model version 2.5 (CM2.5) (Delworth et al. (2012)), employs a high-resolution cubed-sphere finite-volume dynamical core. It closely resembles the atmospheric component of the GFDL Hi-Resolution Forecast-Oriented Low Ocean Resolution (HiFLOR) model, known for producing realistic MH frequencies (Murakami et al. (2015)) and drawing on insights from Chen and Lin (2011) and Chen et al. (2013).

The AM2.5-C360 model effectively simulates realistic hurricane seasonality (Yang et al. (2021)) and responses to climate drivers, such as the El Niño Southern Oscillation (Hsieh et al. (2022)). A set of 10 ensemble members was generated to represent potential scenarios in the North Atlantic from 1871 to 2019. These ensemble members were created under consistent climate and forcing conditions but with different initial conditions, leading to variations in simulated weather. Initial conditions were defined using 10 unique restart files at the beginning of each year, derived from an AM2.5-C360 control simulation with fixed radiative forcings and monthly SST climatology specified by Chan et al. (2021). Climatic forcing from greenhouse gases and aerosols was incorporated through SST forcing.

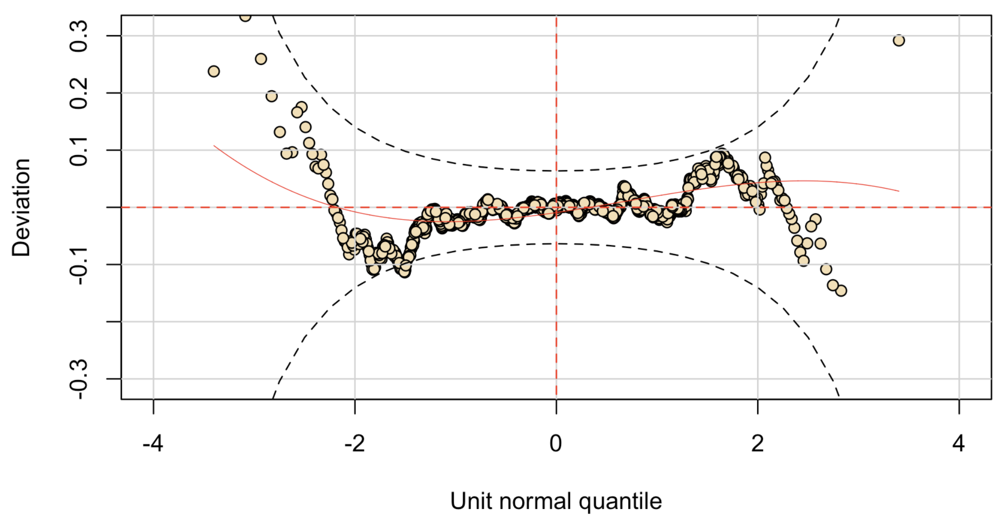

Figure 2: Worm plot of the refined model with four predictors. Since the points lie between the two parabolas, we consider this model to adequately fit the data.

3 Statistical model

3.1 Binomial Regression

The mathematical description of the Binomial regression model follows that of Villarini et al. (2010). We model of the proportion of North Atlantic TCs that transition into a MH using binomial regression, which is a form of Generalized Additive Model (GAM; e.g., Hastie and Tibshirani (1990)). Under this model the number of MHs has a binomial distribution given the total number of TCs. Using the notation in McCullagh and Nelder (1989), we denote Y_1 and Y_2 as two Poisson random variables with means of m_1 and m_2, respectively. The sum of Y_1 and Y_2 (m) follows a Poisson distribution and has a mean equal to $m_1 + m_2$. In our case, m represents the annual basinwide number of TCs, while Y_1 is number of annual MHs. The distribution of Y_1 given m is therefore

$$f(Y_1 = y|\mu) = \frac{\Gamma(m+1)}{\Gamma(y+1)\Gamma(m-y+1)}\mu^y(1-\mu)^{(m-y)}, \tag{6}$$

where $\mu = \mu_1/(\mu_1 + \mu_2)$. The mean and variance of the proportion of TCs that become a MH (Y_1/m) are μ and $\mu(1-\mu)$.

The link function for μ for each year i ($g \in [0,1]$) as a function of the covariates can be written as

$$g(\mu_i) = \beta_0 + \beta_1 h_1(z_{1i}) + \beta_2 h_2(z_{2i}) + ... + \beta_n h_n(z_{ni}). \tag{7}$$

We use a logit link for the link function such that $g(\mu) = \log(\mu/(1-\mu))$, so we write the function of μ_i depending on the covariates as

$$\mu_i = \frac{\exp \beta_0 + \beta_1 h_1(z_{1i}) + ... + \beta_n h_n(z_{ni})}{1 + \exp \beta_0 + \beta_1 h_1(z_{1i}) + ... + \beta_n h_n(z_{ni})} \tag{8}$$

The eight covariates are described below in section 3.2. To the best of our knowledge, there have not been extensive statistical modeling of the fraction of TCs that transition into a MH. Therefore, we do not have many a priori expectations for the most important covariates in our model.

To evaluate the fit of the model and to avoid potential overfitting, we chose the appropriate combinations of covariates for our model using the Akaike information criterion (AIC; Akaike (1974)) and the Schwarz Bayesian criterion [SBC; Schwarz (1978), Rigby and Stasinopoulos (2005), and Stasinopoulos and Rigby (2007)] through a forward selection process. These criteria reflect a balance between model complexity and accuracy. We AIC and SBC are constructed as follows

$$AIC = -2\ln(L) + 2k \tag{9}$$

$$SBC = -2\ln(L) + k\ln(n), \tag{10}$$

where L is the maximum likelihood of the model, k is the number of parameters estimated by the model, and n is the number of observations, which is 10 ensembles $\times$ 140 years $=$ 1490. We will evaluate the tradeoffs between model complexity and precision by fitting the model multiple times with different covariates.

We determine the model's goodness of fit by analyzing the model's residuals. Ideally, the model's residuals should be independent and have identical standard normal distributions (e.g., Rigby and Stasinopoulos (2005)). We assess the mean, variance, kurtosis, and coefficient of skewness of the normalized randomized quantile to obtain a quantitative metric of the residuals and determine of they are approximately normally distributed. Additionally, we visually inspect the residuals using quantile–quantile (Q-Q) plots and worm plots. Q-Q plots where the empirical residuals are approximately linear suggest that the residuals of the model are normally distributed. Worm plots are detrended Q-Q plots, with the shape of the "worm" providing insights into the fit between the data and the chosen distribution. If the worm lies within the parabolas on the plot, it indicates that the data aligns well with the specified distribution.

The calculations and model fittings are performed in R (R Development Core Team 2008) using the gamlss package (Stasinopoulos and Rigby (2007)).

3.2 Covariates

We select two thermodynamic and two dynamic environmental parameters as covariates for the binomial regression (Table 1), all recognized as key drivers of TC development in both the probabilistic framework (e.g., Hsieh et al. (2020)) and GPIs (e.g., Emanuel (2010)). For each parameter, we compute the annual basin-wide mean and standard deviation during the Atlantic TC season (June–November), resulting in a total of eight initial covariates for the model. The most important predictors are identified using a forward selection process, where a predictor is included only if its addition reduces the AIC.

Parameter	Description	Definition	References
Potential Intensity (PI)	Thermodynamic	Measure of maximum possible strength of a storm determined by SSTs and atmospheric temperature	Emanuel (1986a), Emanuel (1986b)
Moist Entropy Deficit (χ)	Thermodynamic	Moist entropy deficit in the middle troposphere, which increases as the middle troposphere becomes drier	Emanuel (2010)
Vertical Wind Shear (v_s)	Dynamic	Difference in wind velocity between two vertical atmospheric levels	Tang and Emanuel (2012) ,Emanuel (2010)
Vorticity (ζ)	Dynamic	Measure of the local rotation in the atmosphere	Hsieh et al. (2020)

Table 1: Environmental parameters used as possible covariates in the Binomial regression model.

4 Results

Table 2 presents the quantitative results of the full eight-covariate model and the refined model obtained through forward selection. Analyzing the residuals indicates that both models adequately fit the data. In both cases, the residuals exhibit properties consistent with a standard normal distribution, with a mean of approximately 0, variance near 1, skewness close to 0, and kurtosis around 3.

Model	**Predictors**	**AIC**	**SBC**	**Mean**	**Variance**	**Skewness**	**Kurtosis**
Full	All	3969.42	4017.18	-0.003	1.01	0.05	2.78
Refined	mean(PI), sd(PI), sd(χ), mean(χ)	3966.02	3992.56	-0.023	1.04	-0.06	2.92

Table 2: Quantitative results for the full eight-covariate model and the 'best' refined model. The first column includes the covariates used, and the refined model covariates are listed in order of relative importance from most important to least important. The next two columns list the AIC and the SBC of each model, and the remaining columns list properties of the model's residuals.

Furthermore, reducing the number of predictors from the full set of eight (Table 1) to the four selected predictors (Table 2) results in decreases in both AIC and SBC. This indicates that the simpler model provides an effective representation of the fraction of TCs that transition into MHs. During the forward selection process, predictors were added in the following order: mean(PI), sd(PI), sd(χ), and mean(χ), reflecting their relative importance in the model. A visual assessment of the refined model using the time series of predictions for the first model ensemble member (Fig. 1), worm plot (Fig. 2), and Q-Q plot (Fig. 3) indicates an adequate fit to the data.

5 Discussion and Conclusion

Based on the strong quantitative results (Table 2) and visual evaluations (Figs. 1, 2, and 3) of the refined model, we conclude that the annual fraction of Atlantic TCs transitioning into MHs can be effectively modeled using a Binomial regression approach. Not all eight predictors listed in Table 1 are necessary to construct a robust model. Through the forward selection process, only thermodynamic variables were included in the final model, highlighting the dominant role of thermodynamic conditions in driving TC intensification into MHs (Bhatia et al. (2018)).

Examining the environmental proxies for N_s and P outlined in equations 2 and 3, we observe that dynamic variables are more critical for TC genesis, as vertical velocity and vorticity are the primary factors in N_s. However, as storms intensify, thermodynamic variables become more influential, given their prominence in P and their exclusive inclusion in the statistical approximation of P_{MH}.

In this study we have developed a statistical proxy for P_{MH} as a function of large-scale environmental parameters. In doing so, we extend the probabilistic framework of Hsieh

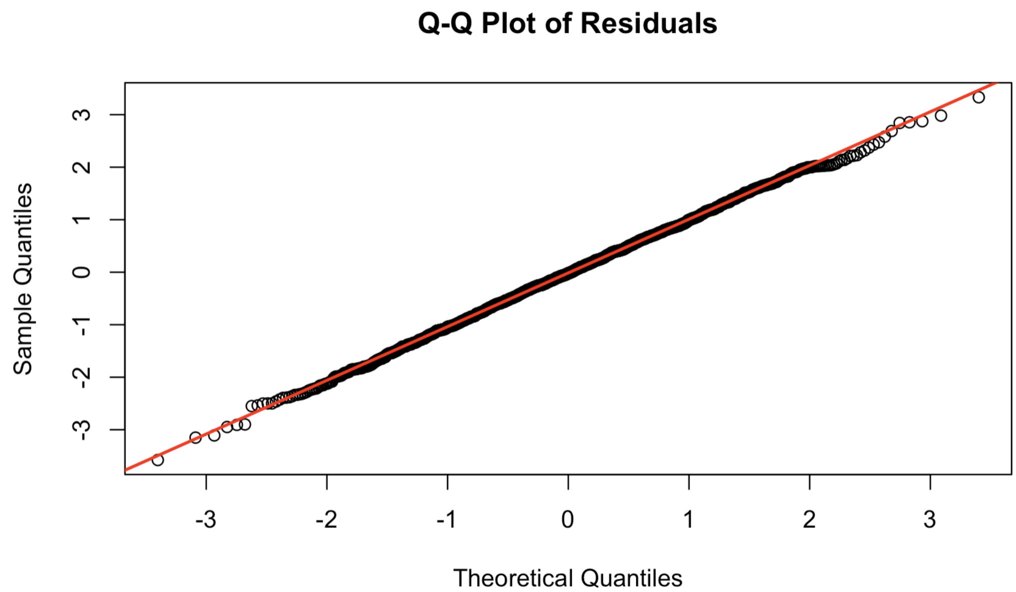

Figure 3: Q-Q plot of the fitted residuals (white dots). Since the residuals exhibit a linear trend, even at the tails, we consider this model to be a strong fit of the data.

et al. (2020) to include the final stage of TC development—transitioning from a TC to a MH.

Future work will focus on:

1. Refitting the Binomial regression model using observational data, such as ERA5 reanalysis, and other climate model output, like the GFDL HiRAM atmosphere-only model, to validate the key predictors influencing the TC-to-MH transition.

2. Reanalyzing the Binomial regression model with AM2.5-C360 data after removing the mean warming trend. This will enable us to assess the relative impact of anthropogenic warming on the TC-MH transition process.

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