Final Project Report

Catherine Jackson (ccj3)

Tue., Apr. 30

1 Introduction

1.1 Storm Surge Variability and Literature Review

Hurricanes represent an ever-present threat to US coastlines, and these events have incredible potential to damage infrastructure and threaten lives. In fact, "Billion-Dollar Weather and Climate Disasters" (2024) found that, when analyzing data from 1980 to 2024, damages from tropical cyclones and severe storms account for 51.8% and 17.3% of climate disaster-related costs respectively. These severe storms and their associated surge events must be better understood in order to protect communities from their damages.

However, both the frequency and characteristics of these storms and their associated surges is made more complex due to spatial dependencies. Needham and Keim (2012) sought to create a storm surge database based on historical activity. They argue that this database can be used by communities to better protect themselves based on historical data. They found that the Central and Western Gulf Coast is particularly vulnerable to hurricanes, both in terms of increased frequency and magnitude, as well as storm surge. Comparatively, the East Coast experienced less frequent and smaller events. Furthermore, Xu et al. (2010) hoped to better understand how the incorporation of multi-scale simulations affected surge predictions, but their results also demonstrated that differences in coastal tophography and bathymetry led to large variations in storm surge events. Islam et al. (2021) found similar results. After including information about translational speed and coastal geometry, the predictions from their surge index became significantly more accurate. In this way, Needham and Keim (2012) demonstrates that there are significant variations along the US coastline based on hurricane magnitude and frequency, and the associated storm surge, due to important climate variations. In addition, Xu et al. (2010) and Islam et al. (2021) demonstrated that including information about coastal geometries and bathymetries is important to accurately modeling and predicting surge.

The image below, from Needham and Keim (2012), visually shows the differences in storm surge across the Southern US coastline based on historical information and data.
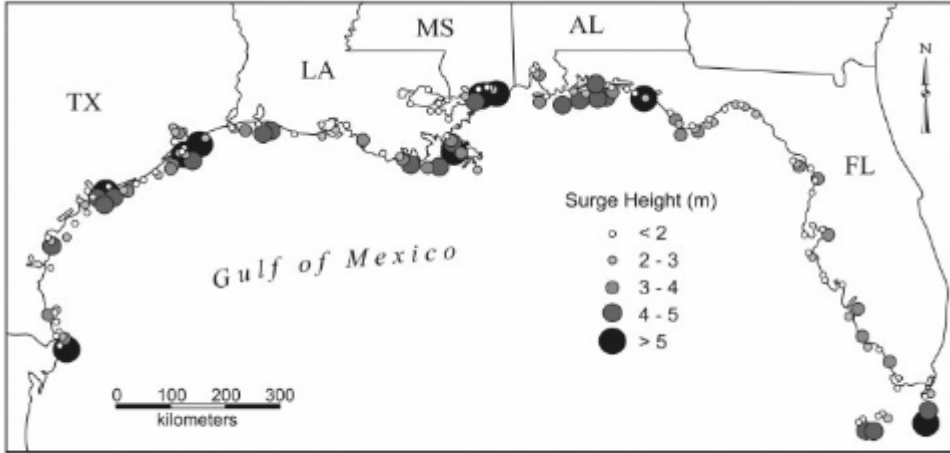
Figure 1. The location and height of the 195 peak storm surges along the US Gulf Coast identified in SURGEDAT.

In conclusion, these papers all demonstrate that physical differences in the coast as well as climate differences in the storms themselves mean that surge behavior is incredibly spatial. To accurately protect communities and analyze risk, the spatial trends must be understood and regional data must be included.

1.2   Problem Statement

In the original risk analysis code, a representative storm surge is randomly generated. This storm surge is represented with a GEV distribution defined by three parameters, each being generated from its own distribution. Most importantly, though, this function was used to apply regardless of the site of interest. The same function was used at many different points across the coastline. As discussed above, however, it is important to include spatial variability given that severe storms and associated surges are highly dependent on the location along the coast and nearby geometry and bathymetry.

The problem that must be addressed, then, is a methodology by which spatial information can be incorporated into the surge function such that the surge is more accurate given the physical characteristics and location of the site.

It is important to address this lack of spatial specificity in the current storm surge generation, within the context of climate risk analysis, as, even if the climate risk assessment methodology is appropriate and efficient, it is dependent on the quality of incoming data. For example, a project could have a statistically sound methodology of determining whether to raise a house given certain flood risks, but if the storm surge distribution used is incorrectly low, the model would incorrectly underestimate the true risk. Improving data inputs improves the decisions produced by this risk analysis tool.

For these reasons, the surge distribution should be as accurate as possible for the specific site of interest. The best methodology to do so is to adjust this distribution towards the observational data from the nearest gage.

1.3 Selected Feature

To address the spatial trends demonstrated in severe storms and associated storm surge, the surge distribution used in risk analysis must be specific to the site of interest. Therefore, the new addition to the decision-support tool must shift the distribution such that it better represents observed data at the nearest gage.

Consequently, this selected feature will be a modification of the code that provides a representative storm surge distribution sample. Note, first, that this code is found in lab code rather than in the HouseElevation.jl file. Consequently, these adjustments are made within the definition of the function itself.

When selecting the best methodology by which the representative distribution can be shifted such that it better represents the behavior at the specific site of interest, I took inspiration from Dr. Doss-Gollin's CEVE 543 class. Bayesian updating allows a distribution to be adjusted as new, observed data is produced. This means that the original surge distribution parameters can be updated using data that comes from the nearest gage, producing distributions more accurate given the physical location of the site.

Again, this improves the climate risk assessment by using Bayesian updating as a methodology to improve the input data. A model is only as reliable as the data it uses to make predictions, so improving the surge based on the actual physical location improves the decision outputs of this model.

2 Methodology

Inspiration for this methodology is drawn primarily from Doss-Gollin (2023). Slides from this course help describe the general process of Bayesian Updating. First, a project might have an original distribution, defined by parameters, each with their own probability distributions. In other words, one of the important parameters might be defined by a Normal distribution (e.g. mean of 5 and standard deviation of 0.5), but it is not a point value. Furthermore, the project might have a reasonable first guess as to what these distributions could be. However, as new data is produced, can be update the beliefs about these distributions so they are more accurate. This is the process of Bayesian Updating.

The slides also define Bayes' rule for distributions as:

$$p(\theta|y) \propto p(y|\theta)p(\theta)$$

Where:

1. $p(\theta|y)$ is the posterior distribution of the parameters given the data

2. $p(y|\theta)$ is the likelihood of the data given the parameters

3. $p(\theta)$ is the prior distribution of the parameters

In other words, the prior is the best guess before any additional data is produced. The likelihood tells us how likely the new observational data is given our beliefs within the prior. We can use the likelihood to update our new beliefs about the distribution.

However, explicitly calculating the posterior can be computationally challenging. Therefore, many models use sampling to reduce this computational load. This concept can be difficult to conceptualize. One analogy is to think of the posterior as a mountainous landscape. Higher peaks represent more likely values of the parameters. The goal is then to find the highest peak. Instead of solving analytically, the model can "walk around" the landscape to find the best values.

Markov Chain Monte Carlo includes many different methods to walk around the landscape, but in general the process is as follows:

1. Start at a random point in the parameter space

2. Propose a new point in the parameter space

3. Determine whether the new point should be accepted or rejected, dependent on the criteria of the specific method

The end goal is then to sample from the most likely values of the parameters to generate a new, more likely distribution of the original parameters. For this project, then, Bayesian Updating will produce new distributions for the three parameters that define the GEV distribution.

2.1 Implementation

Implementation of this Bayesian Updating methodology is inspired by Storopoli (2021) as well as Doss-Gollin (2023). Primarily, original inspiration for the utilization of the Turing package comes from Doss-Gollin (2023) and plotting implementation from Storopoli (2021).

Again, the edits produced during Bayesian Updating change the storm surge distribution package rather than the code in HouseElevation.jl. Consequently, changes can be found here in the template.qmd file.

The following code block demonstrates the creation of the model, using Turing, to sample from the posterior distribution of the parameters. The model is defined as a function, `surge_model`, that takes in the data from the nearest gage. The model then defines the prior distributions for the three parameters of the GEV distribution. The model then loops through the data from the nearest gage, defining the likelihood of the data given the parameters.

1. Define the model as a function which inputs gage data

2. Define the prior distributions for the three parameters of the GEV distribution

3. Loop through the gage data, defining the likelihood of the data given the gage surge heights

```
1   @model function surge_model(y) #<1>
2       ~ Normal(5, 1) #<2>
3       ~ Exponential(1.25)
4       ~ Normal(0.1, 0.05)
5
6       for i in eachindex(y)
7           y[i] ~ GeneralizedExtremeValue( , , ) #<3>
8       end
9   end;
```

Next, observational data is needed to update the distribution. Given that the function predicts the maximum surge heigh for a given year, the data for which the distribution needs to be updated is the maximum surge height for the year. This data is then input into the model to sample from the posterior distribution of the parameters.

Given that storm surges are inherently spatial, the best data to update our parameter distributions is the data from the nearest gage. For this particular project, the nearest gage is located in Galveston, Texas on Pier 21 (National Oceanic and Atmospheric Administration 2024). I was able to download the time series information and isolate the highest storm surge for each month. I then selected the highest storm surge for the year and saved it to the variable dataex. The information from the past 10 years was then fed into my model.

The following cell pulls in the last 10 years of observational data from the Galveston gage. This data is then fed into the model to sample from the posterior distribution of the parameters. The code uses a No U-Turn Sampler (e.g. NUTS) with 1,000 samples.

I have included the original output of the sampler below.

```
1  model = surge_model(dataex)
2  chain = sample(model, Turing.NUTS(), 1000)
```

```
 Info: Found initial step size
     = 0.0015625
Sampling:   0%|                                           |  ETA: 0:01:18Sampling: 100%|

Chains MCMC chain (1000×15×1 Array{Float64, 3}):

Iterations        = 501:1:1500
Number of chains  = 1
Samples per chain = 1000
Wall duration     = 18.57 seconds
Compute duration  = 18.57 seconds
parameters        = , ,
internals         = lp, n_steps, is_accept, acceptance_rate, log_density, hamiltonian_energy, 
```

Summary Statistics

parameters	mean	std	mcse	ess_bulk	ess_tail	rhat	e
Symbol	Float64	Float64	Float64	Float64	Float64	Float64	
	3.7111	0.2126	0.0109	396.6787	481.3676	1.0007	
	0.6521	0.1823	0.0085	462.5793	589.1259	1.0035	
	0.0896	0.0472	0.0017	775.5487	521.8882	1.0036	

1 column omitted

Quantiles

parameters	2.5%	25.0%	50.0%	75.0%	97.5%
Symbol	Float64	Float64	Float64	Float64	Float64
	3.3245	3.5698	3.7087	3.8498	4.1381
	0.3819	0.5283	0.6237	0.7347	1.0692

```
       −0.0068    0.0594    0.0894    0.1224    0.1842
```

2.2 Validation

Validation for this Bayesian Updating is difficult as the true values of the parameters are unknown. However, the updated distributions can be used to find an "expected value" of the storm surge. If this value of storm surge seems reasonable given NOAA gage data, then the Bayesian Updating can be considered successful.

Julia allows users to find the expected value of the distribution using describe(chain) as discussed by Storopoli (2021). In our project, the expected value of the storm surge distribution is 5.31 feet. This value, when compared to the NOAA gage, seems reasonable and lends credibility to the fact that our updating was successful.

However, as mentioned earlier, there are no true distribution parameters. Our parameters can produce results consistent with available historical data, but only relying on data we have seen in recent years raises issues. The data from the Galveston gage only includes the past 10 years. This is a very small sample size, and the data may not be representative of the true distribution. Consequently, the Bayesian Updating may not be as accurate as it could be if more data were available. Furthermore, we determine whether our distribution seems consistent with recent data, but we have no way of determining whether our distribution would be consistent with changes in the future.

3 Results

First, when analyzing the results, both the sampling from the posterior as well as the new distributions of the parameters can be plotted.
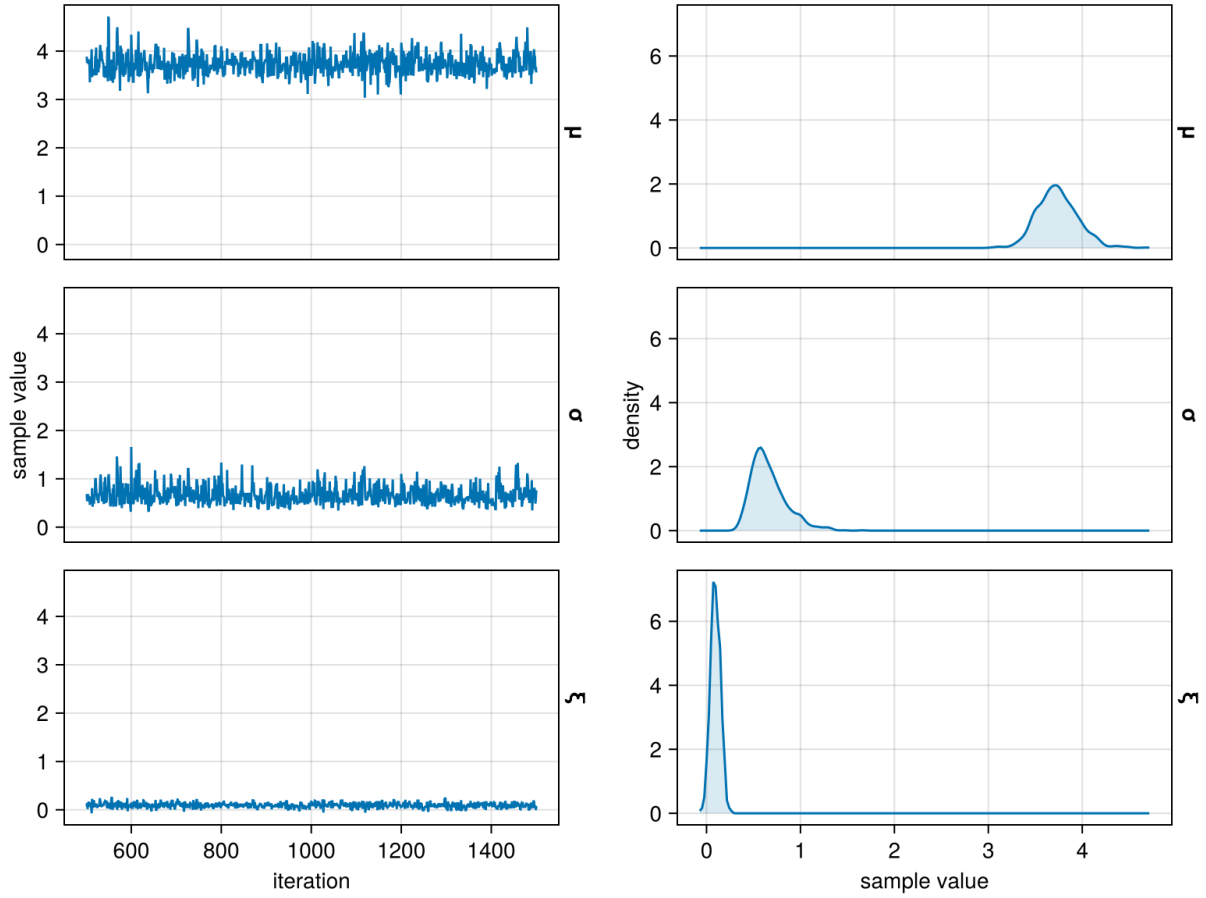
These new distributions, shown in the plots on the right, are more consistent with real, observed data from the Pier 21 gage on Galveston, TX. Again, this improves the spatial accuracy of the storm surge trends.

Then, these new parameter distributions are used to create a new function which now draws a random storm surge given the information from the Bayesin updating.

The difference between the draws from the original GEV distribution and the draws from the Bayesian-updated GEV distribution can be seen below. Note that the figure shows 10 random draws from the different functions.

Original GEV Distributions vs.
Bayesian GEV Distributions
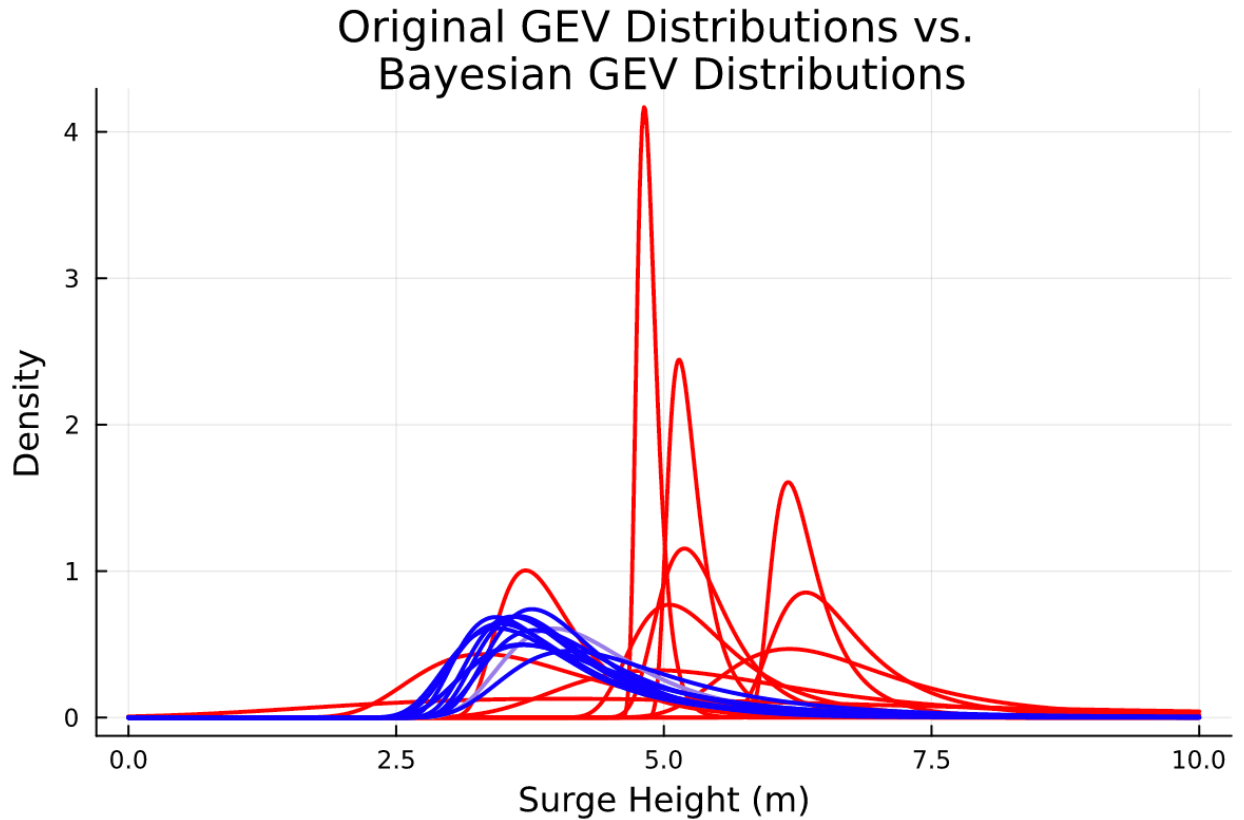
Note that the draws from the bayesian updated GEV distribtion are more concentrated and experience less variability between draws. This represents a key tradeoff. The Bayesian updated distribution is more accurate and consistent given the gage data on which it was trained. This means that it is consistent with the spatial trends in that area, due both to spatial trends in climatology and nearby coastal geometry and bathymetry. However, it is updated only on limited historical data. This means it may not generalize out as well to the future, and it might be less robust to any quick or extreme changes.

This question is part of a larger question of balancing accuracy with historical data and availability to generalize well to other conditions. In other words, it helps represent the balance between bias and variance in the model. The Bayesian updated distribution is more biased towards the historical data, but it may have less variance in the future. The original GEV distribution is less biased towards the historical data, but it may have more variance in the future.

In this way, this Bayesian updating is an important first step in including spatial trends in storm surge into our surge draw function. However, future work must consider the balance between incorporating this spatial trend and representing historical data well with the need to generalize to future conditions.

Hypothetically, the Bayesian updating could be improved by adding an additional parameter which includes non-stationarity. This parameter could represent the change in the distribution over time. This would allow the model to update the distribution based on the most recent data, but also to consider how the distribution might change in the future. This would help the model generalize better to future conditions. On the other hand, this Bayesian updating could be improved by using Bayes' theorem to shift the distribution based on historical data and then adding more variance

back in.

In general, it is a future area of research with signficant potential for exploration.

4 Conclusions

4.1 Discussion

Analyze the implications of your results for climate risk management. Consider the context of the class themes and discuss how your findings contribute to the understanding of climate risk assessment. Identify any limitations of your approach and suggest potential improvements for future work.

4.2 Conclusions

Summarize the key findings of your project and reiterate the significance of your implemented feature in addressing the problem statement. Discuss the broader implications of your work for climate risk management and the potential for further research in this area.

5 References

"Billion-Dollar Weather and Climate Disasters." 2024. National Centers for Environmental Information; https://www.ncei.noaa.gov/access/billions/summary-stats.

Doss-Gollin, James. 2023. "CEVE 543: Data Science for Climate Risk Assessment." Rice University; https://ceve543.github.io/.

Islam, Md. Rezuanul, Chia-Ying Lee, Kyle T. Mandli, and Hiroshi Takagi. 2021. "A New Tropical Cyclone Surge Index Incorporating the Effects of Coastal Geometry, Bathymetry and Storm Information." *Scientific Reports* 11 (16747). https://doi.org/10.1038/s41598-021-96256-0.

National Oceanic and Atmospheric Administration. 2024. "Galveston Pier 21, TX - Station ID: 8771450." National Oceanic and Atmospheric Administration Tides and Currents. https://tidesandcurrents.noaa.gov/stationhome.html?id=8771450.

Needham, Hal F., and Barry D. Keim. 2012. "A Storm Surge Database for the US Gulf Coast." *International Journal of Climatology* 32: 2108–23. https://doi.org/DOI of the paper if available.

Storopoli, Jose. 2021. "Bayesian Statistics with Julia and Turing." https://storopoli.io/Bayesian-Julia.

Xu, Hongzhou, Keqi Zhang, Jian Shen, and Yuepeng Li. 2010. "Storm Surge Simulation Along the u.s. East and Gulf Coasts Using a Multi-Scale Numerical Model Approach." *Ocean Dynamics* 60: 1597–1619. https://doi.org/10.1007/s10236-010-0321-3.