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M3 CHALLENGE®

PREVIEW PAPER: EXCELLENT

The judges noted that this submission had a very good summary. Also, the overall discussion was clear, and the team clearly described their figures. In terms of the modeling the team relied heavily on statistical approaches, but the team did so in a unique way. They developed models based on the data and then used the models to make predictions in a relatively reasonable way.

For example, in question one the team examined the distributions for all of the parks, and attempted to evolve the various distributions in time. For question two they used bootstrapping to overcome the limitations of a small number of data points. On question three they made use of multivariate regression, but they did not make it clear what data sets they used.

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Looking Ahead with the National Park Service

The NPS is committed to ensuring the welfare of the United States's natural resources in order to ensure that all Americans are able to enjoy their nation's environmental treasures. With changes in climate and consumption in recent years, the NPS must adapt its approaches to better suit shifting environmental conditions. This is especially true for coastal regions, which are subject to a number of volatile sea conditions that affect the health of endemic regions.

A major concern for coastal regions is the change in mean sea level (MSL); over time, MSL values are predicted to continually increase. Because MSL is a useful indicator for predicting the health of aqueous environments, coastal regions are at risk of significant economic and environmental harm from the degrading health of their surrounding water. Specifically, the rising sea levels may prompt massive flooding; this will create problems for the NPS, as tourism is reduced and the biodiversity of its parks becomes diminished.

Using information from five nationally representative coastal parks (Acadia National Park, Cape Hatteras National Seashore, Kenai Fjords National Park, Olympic National Park, and Padre Island National Seashore), the risk factors to NPS coastal stations from changes in MSL were monitored using information from the present time, as well as predictions on park risk over ten, twenty, and fifty years. This outlines a clear strategy for NPS action: the agency must act quickly to palliate the risks to coastal parks currently categorized as "high risk." This includes stations like Cape Hatteras National Seashore and Padre Island National Seashore. It should then take precautions for the changes in MSL at locations characterized as "high risk" within ten years of present time (e.g. Acadia National Park). Other stations appear to remain relatively constant, though Cape Hatteras National Seashore shows the possibility of stagnating or diminishing risk over the long run. This suggests that the NPS should prioritize its preservation efforts by focusing on regions similar to Padre Island and Acadia National Park, in that order.

When other calamitous factors are considered, however, statistical modeling prescribes a different course of action. Regions like Cape Hatteras were found to have the greatest climate vulnerability score, combining the risks for wildfires, hurricanes, and all-cause flooding, including inundation not attributable to rises in MSL. Neglecting the safety of such regions could lead to precipitous damage to the Park Service's ability to carry out its goals. It would be remiss, however, to consider working preemptively only in Cape Hatteras-like areas. Areas like Olympic National Park are more likely to experience wildfires than other regions. The NPS should consider focusing most of its holistic preservation efforts in Cape Hatteras-like regions, while providing targeted action in regions with large risk factors for specific natural disasters.

Overall, because of its limited budget, the Park Service will have to determine which regions it believes are the most deserving of intervention. It is the belief of these analysts that regions like Cape Hatteras are most deserving of holistic assistance because of their overall need for assistance for both rising MSL and general natural disasters. Cape Hatteras maintains a high risk in terms of rising MSL for the near future and is the most vulnerable of all representative sample parks studied in this investigation. In addition, it attracts a high number of visitors in comparison to other national coastal stations, suggesting that ensuring the profit potential of the park is a major economic incentive to keeping the station virile and healthy. The overall urgency of the situation at Cape Hatteras National Seashore speaks to the overall need for action in similar regions. Nonetheless, the Park Service must remember that it would be foolhardy to target only Cape Hatteras-like regions without further specialization of climate control operations in regions with specific susceptibility to certain natural calamities.

<u>Background</u>

Since its inception in 1916, the National Park Service (NPS) has been dedicated to the care of our national parks, which attract more than 275 million visitors every year [1]. In order to provide the best visitor experience, the NPS is tasked with the preservation of natural and cultural resources which are increasingly threatened by climate-related events. In particular, rising sea levels are an imminent threat to the visitor experience, as 92% of U.S. coastal national parks are, or will be, affected by sea level rise [2]. Although the natural landscape has been gradually altered by natural events such as erosion, human emissions of greenhouse gases are rapidly changing sea levels around the world. Rising sea levels are linked with recent increases in storm surges and erosion of coastlines, which alter the landscape of coastal national parks by decreasing the amount of park land available for visitors and threatening the visitor experience.

<u>Restatement of Problem</u>

Given the effect of global change factors on park resources and visitor experience, we have responded to the NPS's request to develop a mathematical model to solve the following problems:

1. Define and determine the sea level change risk ratings (high, medium, or low) of five different parks for the next 10, 20, and 50 years.
2. Predict the sea levels of the five parks for the next 100 years.
3. Develop and test a mathematical model that accurately assigns a climate vulnerability score to any NPS coastal unit based on the likelihood and severity of climate-related events (wildfires, hurricanes, and floods) occurring in the park within the next 50 years.
4. Develop a mathematical model that predicts long-term changes in visitor frequency — defined over a span of 50 years — for the five parks to determine where future financial resources should be allocated.

<u>Part I: Tides of Change</u>

Mean sea level (MSL) is defined as "an average level of the surface of one or more of Earth's oceans from which heights such as elevations may be measured." MSL is a reference point, by which the heights of tides and other similar oceanographic statistics may be measured.

Recent analyses by the National Oceanographic and Atmospheric Administration (NOAA) and other watchdog organizations have found that MSL levels have been continually increasing over the past few decades [3]. This poses significant environmental concerns, as a rise in sea levels can disrupt the ecology of an environment through flooding. Changes in ecology can significantly alter the biodiversity and survivability of a region's species, especially those endemic to a given area. For the NPS, there is also a significant economic risk: flooding can reduce visitation and sponsorship of numerous parks, reducing the revenue of the American government.

A. Restatement of Problem

In order to prepare for the serious challenges posed from rising MSL across the United States, the NPS must categorize the economic, environmental, and other ambient risks posed to its parks. This involves initial categorization of the parks into three risk categories: low, medium, and high.

As a sample, the risk factors for five national parks were categorized using historical data from the NOAA. These locations included Acadia National Park (Bar Harbor, ME), Cape Hatteras National Seashore (Oregon Inlet Marina, NC), Kenai Fjords National Park (Seward, AK), Olympic National Park (Port Angeles, WA), and Padre Island National Seashore (Corpus Christi, TX).

B. Categorization Procedure

To categorize the parks, historical data on annual change in MSL (*mm/yr*) was retrieved for each park. This involved analysis of the change in MSL per reporting station closest to each park. Using the NOAA reporting system, retrieval was facilitated by the provided station IDs for each park locality.

National Park	**Station ID**
Acadia National Park	8413320 (Bar Harbor, ME)
Cape Hatteras National Seashore	8652587 (Oregon Inlet Marina, NC)
Kenai Fjords National Park	9455090 (Seward, AK)
Olympic National Park	9444090 (Port Angeles, WA)
Padre Island National Seashore	8779750 (Padre Island, TX)

Figure 1: NOAA coastal station identification for sample parks

The changes in MSL for these regions was then identified in a table of ΔMSL for all NOAA coastal stations. Because large positive changes in MSL pose equal environmental and economic changes to large negative changes (direction of change in MSL), absolute values of all changes in MSL were then analyzed.

Using the absolute values of the changes in MSL, a density plot was created to analyze the distribution of the change in sea level values. The thirty-third ($33.\overline{3}$%) and sixty-seventh ($66.\overline{6}$%) percentile values of $|\Delta MSL|$ were found to create three categories: low risk (low extreme-$33.\overline{3}$%), medium risk ($33.\overline{3}$%-$66.\overline{6}$%), and high risk ($66.\overline{6}$%-high extreme) for the parks.

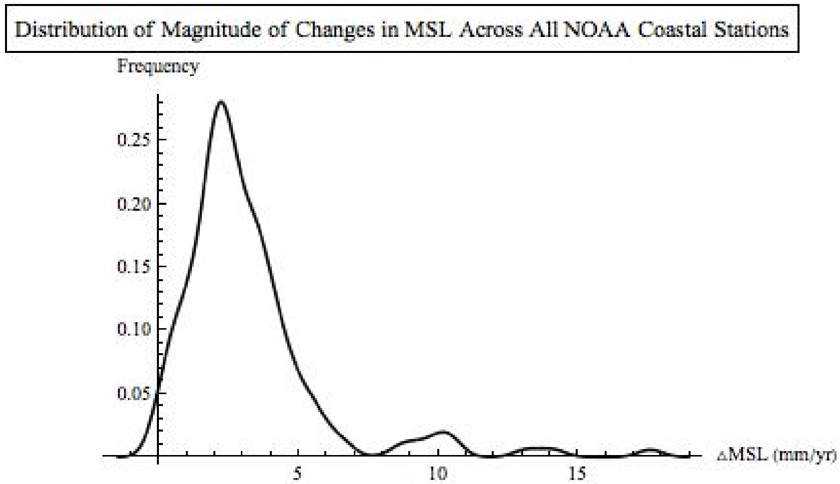

Figure 2: The density of the absolute values of changes in mean sea level were used to plot a distribution for all NOAA coastal stations.

Minimum (*mm/yr*): 0.040, Q_1 (*mm/yr*): 1.92, $\hat{x}$ (*mm/yr*): 2.56, $\bar{x}$ (*mm/yr*): 3.21, Q_3 (*mm/yr*): 3.81, Maximum (*mm/yr*): 17.59

Categorization of Risk	**Interval** $\lvert \Delta MSL \rvert$ **(*mm/yr*)**
Low	[0.04, 2.04)
Medium	(2.04, 3.40)
High	(3.40, 17.59]

Figure 3: Defined intervals of sea level change based on percentile breakdowns of ΔMSL

National Park	$\lvert \Delta MSL \rvert$ **(*mm/yr*)**
Acadia National Park	2.18
Cape Hatteras National Seashore	3.84
Kenai Fjords National Park	2.62
Olympic National Park	0.14
Padre Island National Seashore	3.48

Figure 4: Values of ΔMSL for the sample parks

Using these values and the intervals in Figure 3, the five parks were categorized by risk:

National Park	**Risk Categorization**
Acadia National Park	Medium
Cape Hatteras National Seashore	High

Kenai Fjords National Park	Medium
Olympic National Park	Low
Padre Island National Seashore	High

Figure 5: Categorization of sample parks using $|\Delta MSL|$ values

C. Predicting Long-Term Risk

Using the categorizations above, the changes in the risk for the sample parks over time can be predicted by looking at the changes in $|\Delta MSL|$ over ten, twenty, and fifty years.

In a recent study entitled, "Nonlinear Change in Sea Level Observed at North American Tide Stations," oceanographers John D. Boon and Molly Mitchell evaluated the changes in ΔMSL for forty-four NOAA coastal stations by looking at the mean $б_2$, or "acceleration" values (in *mm/yr^2*) for the mean sea levels.[4] Forty-three stations for which current data on MSL were available were included in an analytic evaluation of $|\Delta MSL|$. This allowed for re-categorization of the sample stations over time.

Using the forty-three data points, a density plots was created to find the current distribution of $|\Delta MSL|$ values for the stations included in Boon's and Mitchell's study. This served as a standard of comparison, allowing a comparison of the distributions of $|\Delta MSL|$ over time. This nationally representative sample allowed for the creation of new percentile intervals to characterize the risks for the sample parks over time, as time-progressed data was plotted.

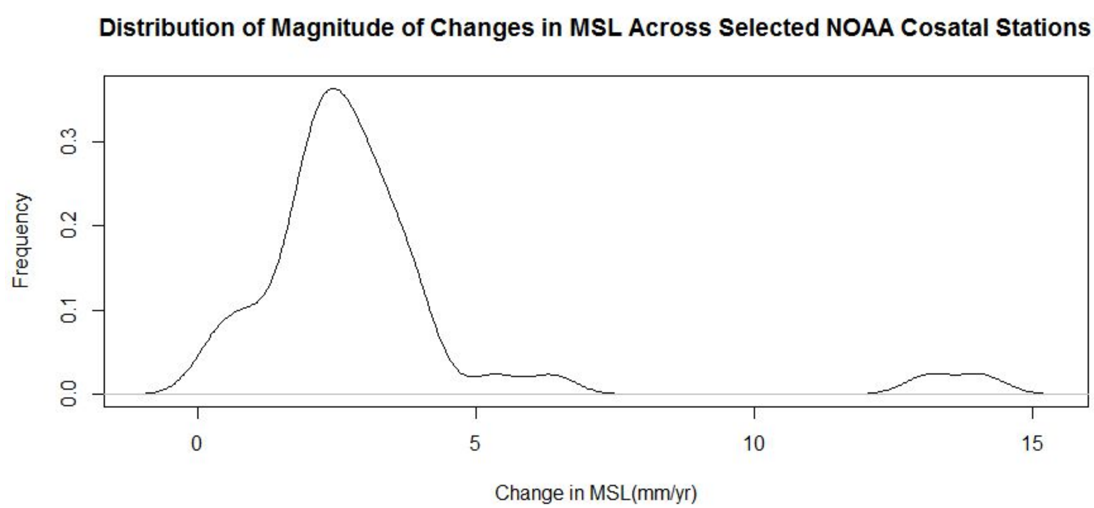

Figure 6: The density of the absolute values of changes in mean sea level were used to plot a distribution for the selected NOAA coastal stations. [EDIT: Cosatel=Coastal]
Minimum (*mm/yr*): 0.230 , Q_1 (*mm/yr*): 2.045, $\widehat{x}$ (*mm/yr*): 2.650, $\bar{x}$ (*mm/yr*): 3.109, Q_3 (*mm/yr*): 3.370, Maximum (*mm/yr*): 14.10

Percentile intervals were calculated; categorizing the data into terciles allowed for the creation of the low, medium, and high risk classes.

Categorization of Risk	**Interval** $|\Delta MSL|$ **(*mm/yr*)**
Low	[0.23, 2.19)
Medium	(2.19, 3.14)
High	(3.14, 14.10]

Figure 7: Defined intervals of sea level change based on percentile breakdowns of ΔMSL for selected stations

National Park	**Risk Categorization**
Acadia National Park	Low
Cape Hatteras National Seashore	High
Kenai Fjords National Park	Medium
Olympic National Park	Low
Padre Island National Seashore	High

Figure 8: Categorization of sample parks using $|\Delta MSL|$ values for selected NOAA coastal stations

The use of "acceleration" values allowed for the prediction of $|\Delta MSL|$ values after ten years by multiplying the number of years by the mean β_2 scores. Thus, a distribution of $|\Delta MSL|$ values was plotted to observe the changes in $|\Delta MSL|$ intervals after ten years:

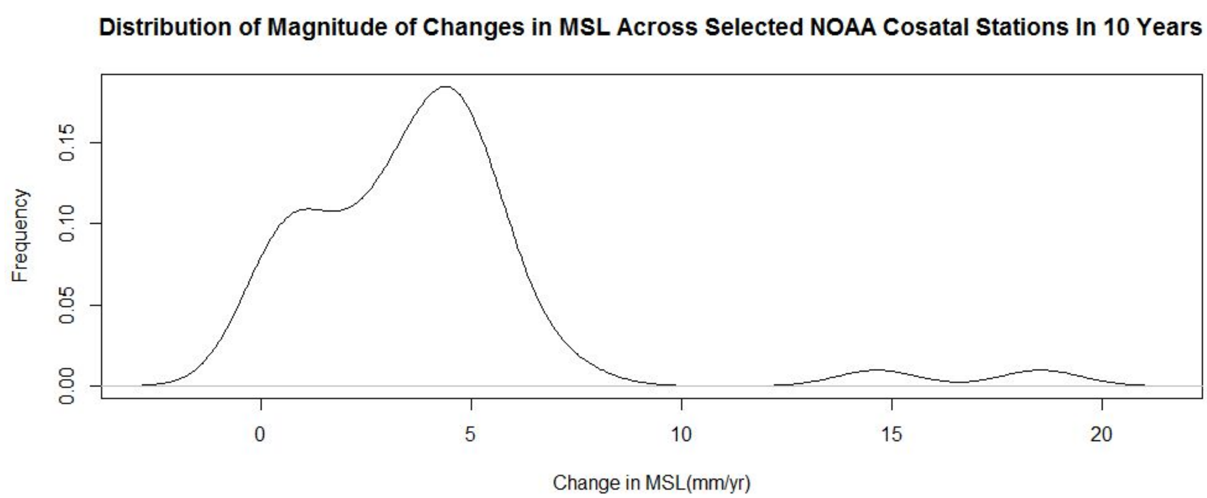

Figure 9: The density of the absolute values of changes in mean sea level were used to plot a distribution for the selected NOAA coastal stations after ten years.

Minimum (*mm/yr*): 0.06 , Q_1 (*mm/yr*): 1.82, $\hat{x}$ (*mm/yr*): 3.91, $\bar{x}$ (*mm/yr*): 3.95, Q_3 (*mm/yr*): 4.84, Maximum (*mm/yr*): 18.55

Categorization of Risk	**Interval** $\|\Delta MSL\|$ **(*mm/yr*)**
Low	[0.06, 2.87)
Medium	(2.87, 4.64)
High	(4.64, 18.55]

Figure 10: Defined intervals of sea level change based on percentile breakdowns of ΔMSL for selected stations after ten years

To predict the effect of time on the sample parks, "acceleration" values for the nearest coastal reporting station to each location were used to "age" the $|\Delta MSL|$ values for the five regions. The $|\Delta MSL|$ at different intervals of time was computed as follows:

$$|\Delta MSL|_{\text{new}} = ||\Delta MSL|\,current\; + \; t(acceleration)| \quad (t \text{ in number of years})$$

Sample Park	**Predictor Reporting Station**
Acadia National Park (Bar Harbor, ME)	Portland, ME (8418150)
Cape Hatteras National Seashore (Oregon Inlet Marina, NC)	Wilmington, NC (8658120)
Kenai Fjords National Park (Seward, AK)	Yakutat, AK (9453220)
Olympic National Park (Port Angeles, WA)	Seattle, WA (9447130)
Padre Island National Seashore (Padre Island, TX)	Rockport, TX (8774770)

Figure 11: Predictor stations used to "age" the $|\Delta MSL|$ values for the sample parks

After ten years, the following mean values were derived:

National Park	$\|\Delta MSL\|$ **(*mm/yr*)**
Acadia National Park	4.74
Cape Hatteras National Seashore	4.63
Kenai Fjords National Park	3.07
Olympic National Park	0.85
Padre Island National Seashore	5.53

Figure 12: Predicted values of $|\Delta MSL|$ for the sample parks after ten years

Using these values and the intervals in Figure 3, the five parks were categorized by risk:

National Park	Risk Categorization
Acadia National Park	High
Cape Hatteras National Seashore	Medium
Kenai Fjords National Park	Medium
Olympic National Park	Low
Padre Island National Seashore	High

Figure 13: Categorization of sample parks using $|\Delta MSL|$ values after ten years

The above procedure was repeated to find the distribution, percentile intervals, and sample categorizations of $|\Delta MSL|$ values over twenty and fifty years.

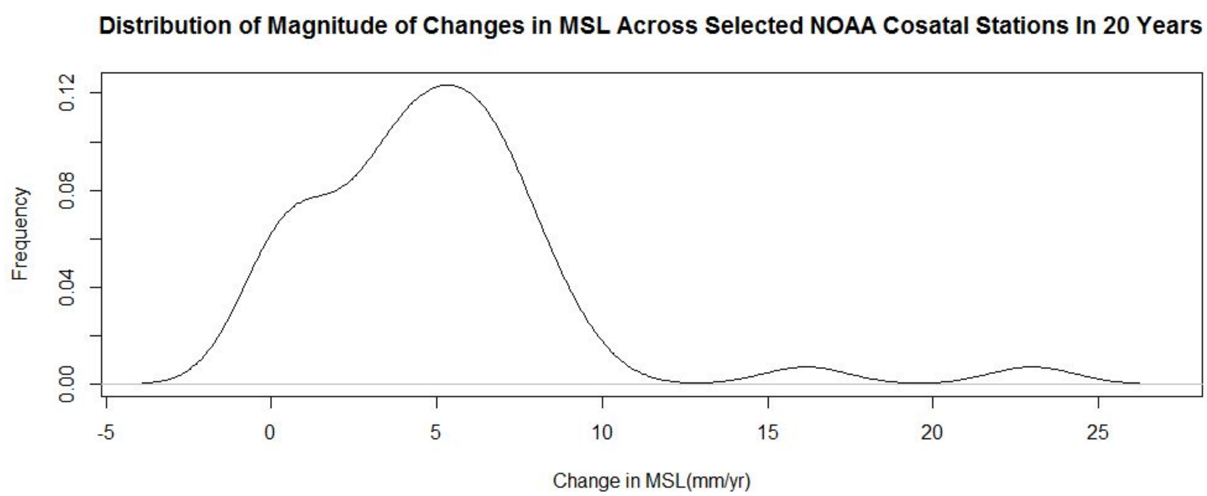

Figure 14: The density of the absolute values of changes in mean sea level were used to plot a distribution for the selected NOAA coastal stations after twenty years.
Minimum (*mm/yr*): 0.01 , Q_1 (*mm/yr*): 2.46, $\widehat{x}$ (*mm/yr*): 4.61, $\overline{x}$ (*mm/yr*): 5.03, Q_3 (*mm/yr*): 46.57, Maximum (*mm/yr*): 23.00

Categorization of Risk	**Interval** $|\Delta MSL|$ **(*mm/yr*)**
Low	[0.01, 3.52)
Medium	(3.52, 6.02)
High	(6.02, 23.00]

Figure 15: Defined intervals of sea level change based on percentile breakdowns of ΔMSL for selected stations after twenty years

National Park	$\|\Delta MSL\|$ **(*mm/yr*)**
Acadia National Park	7.30
Cape Hatteras National Seashore	5.42
Kenai Fjords National Park	3.52
Olympic National Park	1.84
Padre Island National Seashore	7.58

Figure 16: Predicted values of $|\Delta MSL|$ for the sample parks after twenty years

National Park	**Risk Categorization**
Acadia National Park	High
Cape Hatteras National Seashore	Medium
Kenai Fjords National Park	Medium-High
Olympic National Park	Low
Padre Island National Seashore	High

Figure 17: Categorization of sample parks using $|\Delta MSL|$values after twenty years

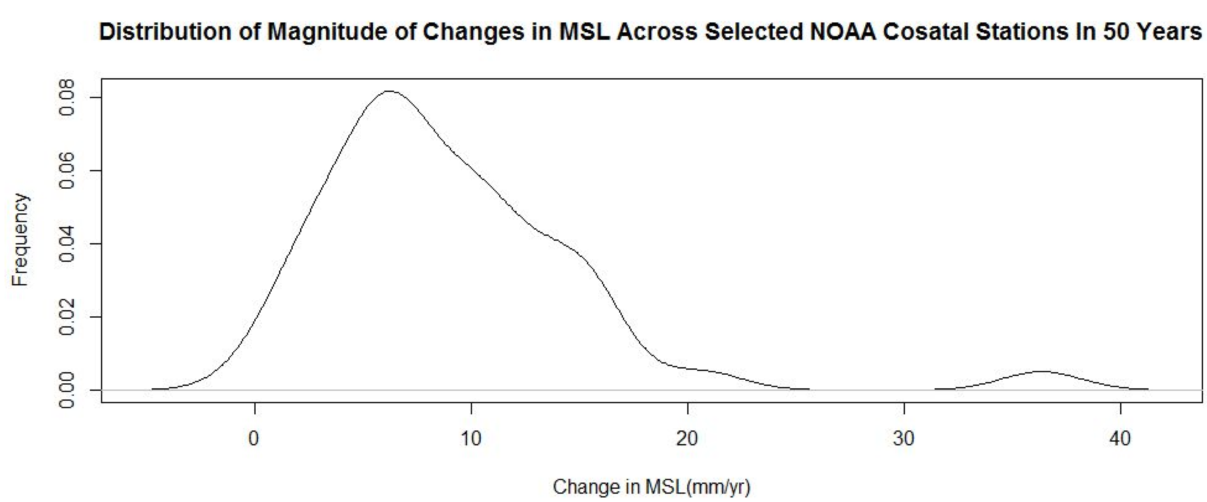

Figure 18: The density of the absolute values of changes in mean sea level were used to plot a distribution for the selected NOAA coastal stations after fifty years.

Minimum (*mm/yr*): 0.37 , Q_1 (*mm/yr*): 5.55, $\hat{x}$ (*mm/yr*): 7.43, $\bar{x}$ (*mm/yr*): 9.03, Q_3 (*mm/yr*): 11.37, Maximum (*mm/yr*): 36.35

Categorization of Risk	**Interval** $\|\Delta MSL\|$ ***(mm/yr)***
Low	[0.37, 6.14)
Medium	(6.14, 10.69)
High	(10.69, 36.35]

Figure 19: Defined intervals of sea level change based on percentile breakdowns of ΔMSL for selected stations after fifty years.

National Park	$\|\Delta MSL\|$ ***(mm/yr)***
Acadia National Park	14.99
Cape Hatteras National Seashore	7.79
Kenai Fjords National Park	4.87
Olympic National Park	4.81
Padre Island National Seashore	13.73

Figure 20: Predicted values of $|\Delta MSL|$ for the sample parks after fifty years

National Park	**Risk Categorization**
Acadia National Park	High
Cape Hatteras National Seashore	Medium
Kenai Fjords National Park	Low
Olympic National Park	Low
Padre Island National Seashore	High

Figure 21: Categorization of sample parks using $|\Delta MSL|$values after fifty years

D. Assumptions

1. For the "aging" of the risk categorization among the sample parks, we assumed that coastal stations close to the national parks would provide accurate estimates of MSL. Because of location along the same coastline, this assumption allowed us to use existing data given the constraints of the problem.
2. The first categorization of risk with current data relied on the assumption that ΔMSL, or the first derivative of MSL with respect to time, was linear. This was assumed in order to prevent the "aging" factor (as explained in later analysis of the problem) from occluding the continuous analysis of the present conditions to categorize the sample parks.

3. With regard to the mean sea level trend, "low," "medium," and "high" categorizations were generated using the density plots and data tables presented above. The thirty-third and sixty-sixth percentiles of this information were used to categorize the data; the assumption that terciles would allow for three categories was a major assumption employed throughout the risk analysis.

E. Limitations of Model

Although this model appears to make definite conclusions for the sample parks, it is limited in its applicability as time increases. Because, on the whole, the number of parks characterized into the high risk category increases with time, the percentile ranks of the $|\Delta MSL|$ values sharply rise in comparison to the change in the $|\Delta MSL|$ for the parks. This means that the system of categorization, as time substantially increases, must be readjusted to prevent all parks from continually placing within the high risk category. In other words, because the change in the percentiles is much higher than the change in $|\Delta MSL|$ for the sample parks over time ($\frac{d(percentile)}{dt} > \frac{d(|\Delta MSL|)}{dt}$), this discrepancy must be resolved for the model to function properly for one hundred years or more.

In addition, there is error in this model which prevents it from functioning with full accuracy. First, because there are approximately one hundred more data points included in the large data set used in the first categorization of the parks, the results of that interpretation differ from that used in the previous literature. This discrepancy in data accounts for the observed dichotomies in the percentile intervals used for categorization at present time. In addition, because of the absolute values used throughout the paper, the consistency of the model over time required that negative changes in "acceleration" eventually result in positive ΔMSL statistics. The flaws in this approach are evident in the change in categorization of Kenai Fjords National Park, which saw a rise in risk until fifty years time. At this point, risk fell because of the effects of considering only magnitude. However, not considering absolute values would imply that negative changes in ΔMSL are less risky than positive fluctuations.

F. Summary and Verification of Model

Based on the data above, the $|\Delta MSL|$ values for the sample parks indicates that rising mean sea levels poses a problem to the NPS. Over time, as median $|\Delta MSL|$ levels appear to increase, more parks appear to become high risk. This indicates that the NPS must prepare for the environmental impacts of increasing sea levels, as more of its property becomes subject to economic and environmental harm. Analyzing the distributions reaffirm that this becomes increasingly pressing over time: the graphs become more left-skewed as the time factor increases, indicating rising sea levels and risk. Even with the limitations and assumptions of this model, this conclusion holds true.

To confirm the reliability of this model, future investigations should attempt to generate a function-based model for this information. This would ensure that sensitivity analysis could be performed on the model, allowing for support that the current model will not work for extended periods of time. The issues with magnitude comparison should also be considered in future work with this data.

<u>Part II: The Coast is Clear?</u>
Changes in climate can create serious problems for national parks across America, as natural disasters can devastate their environment and lead to a decrease in visitors. For coastal units specifically, the risks are heightened: in addition to wildfires, hurricanes and rising sea levels also pose significant risks to their ecosystems.

A. Restatement of Problem
The NPS must prepare itself for the event of a natural disaster across its national parks; however, this necessity is heightened for the eighty-eight coastal units it protects across the United States. Although the climate is relatively predictable for these regions, it is difficult to model the probability and severity of calamities like wildfires and hurricanes. With rising sea levels across the world, this is also a concern among geologists.
Thus, the need for a model associating the severity and probability of wildfires and hurricanes can help the NPS assess the vulnerability of its coastal units. Using the five sample parks from the above analysis allows for the allocation of vulnerability scores to the representative coastal units, extending the previously-developed model of risk.

B. Assumptions
1. The damage that hurricanes inflict on coastal areas is directly proportional to the average speed of their sustained winds and hence their storm categories.
2. The event of hurricane and wildfire occurrences is strictly stochastic, meaning that the frequency of previous occurrences does not impact the probability of an occurrence. Hurricane and wildfire occurrences are defined to be random variables.
3. The probabilities of hurricane and wildfire occurrences can be modeled under a Poisson distribution. This necessitates that two hurricane events cannot occur simultaneously at a single location, that hurricane events occur independently, and that the probability of a hurricane event in a given time interval is proportional to the length of the interval.
4. Hurricane activity remains constant over time, since the use of various observation methods over time has made it difficult to know whether hurricane activity has increased over time [19].
5. Mean Higher High Water, the average of the higher high water height of each tidal day, is the threshold at which flooding can occur. Epoch.[7].
6. Hurricanes, wildfires, and floods inflict similar levels of damage on a given coastal unit of fixed area. These damage levels are indistinct from each other.

C. Scoring Procedure
In order to prepare the NPS for the probability of a natural calamity at one of its coastal units, it is important to understand the vulnerability of the unit to various natural disasters.

1. Hurricanes
Previous literature notes the applicability of the Poisson distribution in modeling the probability of experiencing a hurricane in a given amount of time. Given the probability mass function for this distribution, Poisson-based statistics must meet the following assumptions:
1. The probability of observing a single event over a restricted interval is proportional to the size of that interval.

2. All events in a given frame are mutually exclusive.
3. The probability of an event occurring within a given frame remains constant when the interval is changed .
4. Events occurring in different intervals are mutually exclusive [5].

$$P(X = x) = \frac{\lambda^x e^{-\lambda}}{x!}$$

Figure 22: The probability mass function for the Poisson distribution

The expected value, or long-run mean, of the Poisson distribution is **λ**. The vulnerability can be estimated by using the expression $v = \sum p_k s_k$, where p_k denotes the probability of a hurricane occurring and s_k denotes the intensity of the hurricane. Intensity is measured on a scale from one to eight assigning values appropriately: H5-8, H4-7, H3-6, H2-5, H1-4, TS-3, TD-2, ET-1 (a standard scale for hurricane intensity). **λ** is the average number of hurricanes per year.

The population mean for intensity was computed using a bootstrapping method. By running two thousand iterations, we were able to obtain the following average bootstrapped intensities, denoted as $\mathbf{Intensity}_{\mathbf{Bs\_Avg}}$:

National Park	$\boldsymbol{\lambda}_{\mathbf{Bs}}$ (hurricanes/year)	$\mathbf{Intensity}_{\mathbf{Bs\_Avg}}$	**Vulnerability**
Acadia NP	0.284	1	0.286
Cape Hatteras NS	1.55	2.84	4.32
Kenai Fjords NP	0	N/A (No hurricanes)	0
Olympic NP	0	N/A (No hurricanes)	0
Padre Island NS	0.52	3.53	1.84

Figure 23

2. Wildfires

Similar to hurricanes, previous literature has concluded that a Poisson distribution is an effective mechanism for modeling the probability of experiencing a wildfire in a given period of time [6].

Data from the National Park Service provides wildfire data from 1997 to 2016; however, only data from 2003 to 2016 includes fire condition classes ranging from 1-3, which were used to determine intensity. Following an identical methodology to hurricanes, **λ** as a bootstrapped intensity (n=2000 iterations) were computed. The vulnerability was then computed as a product of these two factors.

National Parks	$\boldsymbol{\lambda}_{Bs}$ (wildfires/year)	**Intensity**$_{Bs\_Avg}$	**Vulnerability**
Acadia NP	3.09	1.77	5.47
Cape Hatteras NS	4.68	1.88	8.80
Kenai Fjords NP	N/A	N/A	N/A
Olympic NP	17.86	1.05	18.75
Padre Island NS	2.75	1.15	3.16

Figure 24

3. Flooding

Similar to the prior two natural calamities, a Poisson distribution is an effective method to analyze the probability of a flood event in a given period of time [19]. Data from NOAA's Inundation Analysis tool provides recent data on $\boldsymbol{\lambda}$ based on Mean Higher High Water (MHHW) over the past five years. The amount of flooding events are dependent on water levels that exceed MHHW. **Intensity**$_{Median}$ is the mean height exceeded over MHHW. Vulnerability, again, is a product of these two factors.

National Park	$\boldsymbol{\lambda}$ (flooding events/year)	**Intensity**$_{Median}$	**Vulnerability**
Acadia NP	304	0.23	68.4
Cape Hatteras NS	438	0.09	40.73
Kenai Fjords NP	164	0.19	31.16
Olympic NP	166	0.10	16.6
Padre Island NS*	114	0.05	5.7

Figure 25

* Note: Due to limited availability of MHHW data for the Padre Island NS, Rockport, TX (8774770), a nearby reference point, is used to calculate flooding data for the seashore instead.

4. Other Factors

During the course of our research we determined a number of other factors that may impact NPS coastal units, including air quality, temperature, and heat index. Due to time constraints we were unable to integrate them into our final model.

C. Model Integration

In order to determine a single **climate vulnerability score (CVS)** that can be applied to all of the NPS's eighty-eight coastal units to predict vulnerability over the next fifty years, we applied a weighted risk model to the risk factors determined above. The model follows the general form as follows:

$$\text{CVS} = \frac{w_1 p_1 s_1 + w_2 p_2 s_2 + \ldots + w_n p_n s_n}{n}$$

where w_k is the weight of the factor, p_k is the probability of the factor's occurrence over the next 50 years, and s_k is the average predicted intensity of the factor, such that $0 \leq p_k s_k \geq 1$. By bounding $p_k s_k$, we ensure a consistent range between factors which we can then weight using the weight coefficients.

In order to ensure that $p_k s_k$ (for convenience simplified to v_k, vulnerability) fits within the range, we normalized and rescaled each factor's set of vulnerabilities to produce a v', which is bounded between 0 and 1:

$$v' = \frac{v - \min(v)}{\max(v) - \min(v)}$$

Since we assumed that all examined factors had equal weights, w_k can be replaced with

$$w_k = \frac{1}{n}$$

for each factor. By applying this normalization function, scaled vulnerabilities for each factor for each park can be determined.

A total CVS score can then be computed for each park, as depicted in the table below.

National Park	**Hurricane Scaled Vulnerabilit y**	**Wildfire Scaled Vulnerability**	**Flooding Scaled Vulnerability**	**Computed CVS Score [0, 1] (given $w_k = 1/n$ for all factors)**
Acadia NP	0.0662037	0.1479619	1.0000000	0.4047218667
Cape Hatteras NS	1	0.3614958	0.5586922	0.6400626667
Kenai Fjords NP	0	N/A	0.4060606	0.1353535333
Olympic NP	0	1	0.1738437	0.3912812333
Padre Island NS	0.4259259	0	0.0000000	0.1419753

Figure 26

D. Limitations of Model

The following weaknesses of our model can be improved upon:

1. Vulnerability can be defined as a function of not only sensitivity but also exposure and adaptive capacity, two commonly incorporated factors that our model does not take into account. A national park that is exposed to many natural disasters may demonstrate high adaptive capacity, meaning that the park is more resilient (i.e., loss of biodiversity is comparatively smaller) and thus has a lower vulnerability score than our model assigns.
2. Our model does not explore the effects of climate-related events on vulnerable and exposed elements such as plant and animal species.
3. Other climate-related events such as droughts and tornadoes that our model does not incorporate may have a significant impact on the climate vulnerability scores of national parks. Especially in regions of the U.S. that experience particular natural disasters more frequently, our model may assign inaccurate vulnerability scores to national parks in these regions. For example, a national park in the Midwest that regularly incurs tornadoes but not hurricanes may be inaccurately assigned a low vulnerability score. Since our model extends only to coastal park units, this limitation should have minimal impact.
4. Our model does not explore the impact of human activities such as mining and logging on the climate vulnerability of a park. Realistically, human activities significantly alter the natural landscapes of national parks, often making them more vulnerable to natural disasters.
5. We assigned equal weights to each disaster when calculated the climate vulnerability score. In doing so, we assumed that each disaster has the same environmental and cultural impact on a given national park when in reality different disasters inflict different levels of damage to property.

With some additional work, these factors could be included in our model but were kept out for simplicity.

E. Summary and Verification of Model

Our model computes the climate vulnerability scores for five national parks based on their respective vulnerabilities to hurricanes, wildfires, and floods. These disaster-related vulnerabilities were then computed by summing the products of the probability and the severity of the climate-related event. To find the climate vulnerability score for one of the eighty-eight coastal park units, simply add the vulnerabilities of the park due to the three climate-related events we assessed. This straightforward yet generalizable model can then be verified via computer simulations of projected climate vulnerability scores of various hypothetical coastal park units. Adjusted parameters would include the mean sea levels, the mean higher high water levels, and the frequencies and intensities of wildfires and hurricanes in the simulated parks.

Part III: Let Nature Take Its Course?

Under the Keynesian theory of macroeconomic spending, the government often enters a deficit in order to the finance the vastness of its economic expenditures. This results in difficulty passing Congressional budget resolutions. Thus, government shutdowns occur when budget resolutions are not passed before the start of the upcoming fiscal year on October 1.

For the National Park Service, this suggests that the lack of agreement can restrict the spending capacity of the agency. This means the NPS must prioritize its spending on the parks that most need its attention. Among the coastal units, this need is heightened due to the complexity of maintaining land even more exposed to natural elements.

A. Restatement of Problem

Because of budget constraints, the NPS must prioritize its spending. For its coastal units, this involves an in-depth analysis of vulnerability, risk, and revenue potential from tourism. Using this information, the Park Service should be able to efficiently allocate its time and financial resources to dealing with endemic issues across the nation.

To assist the NPS in making these conclusions, the representative sample of the five parks used above can also be analyzed. The precedent from this analysis can help influence how the NPS evaluates its national holdings.

B. Assumptions

1. It is not feasible to make recommendations on the level of detail that the NPS delves into in their annual budget. Instead, a reasonable analysis can be focused on three general areas to which the NPS can devote funding:
    a. Disaster relief
    b. Infrastructure improvement
    c. Tourism
2. We assume that social, economic, and political factors remain constant and do not impact visitorship. For example, inflation rates are assumed to be fixed over the given time span, as visitorship may decline as inflation rates rise.
3. We assumed that all factors that contributed to the model were linear in nature. This was founded upon the moderately significant regression coefficients from each factor.

C. Exploration and Model Development

An evaluation of the visitorship for the five selected NPS coastal units showed that there is no apparent overarching trend.

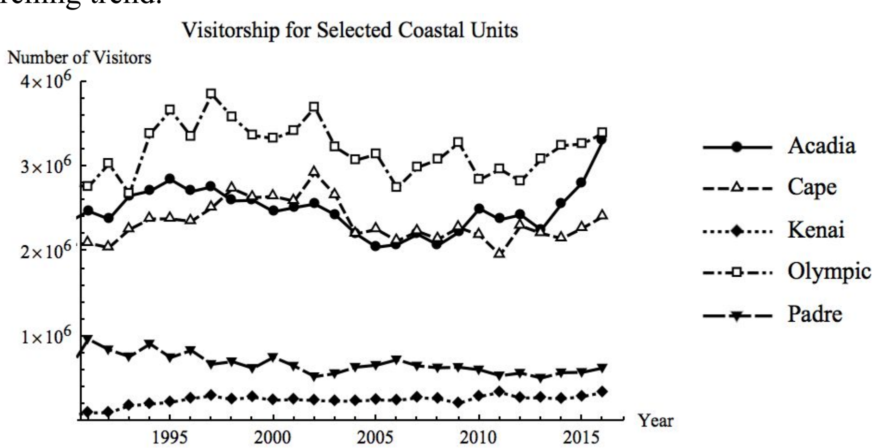

Figure 27: Trends of visitorship over the past 20 years for each national park.

We then examined the potential correlation between visitorship and a number of other climate-related factors in each national park.

Though in isolation these factors had limited correlation, a least squares multiple regression of all of these factors combined produced an R^2 value of 0.93. The generated equation can be used to model the number of visitors to any park any number of years in the future.

$$\text{Number of Visitors} = -9551.908293 * \text{Average Temperature} + 82075.51261 * \text{Number of Wildfires} + 180448.7 * \text{Air Quality Index} - 173834 * \text{Number of Hurricanes} - 63232.7 * \text{Heat Index} + 147392.5 * \text{Year} - 3 * 10^8$$

After computing our multiple regression, we then computed several single variable regressions of all our climate-related factors with the year. This resulted in a equation in terms of only one variable, year.

$$\text{Number of Visitors} = -9551.908293 * (-0.1183649123 * \text{Year} + 284.2605649) + 82075.51261 * (-0.002597402597 * \text{Year} + 5.49350649) + 180448.7 * (-0.3584307172 * \text{Year} + 760.53439) - 173834 * (-0.002597402597 * \text{Year} + 5.49350649) - 63232.7 * (0.132339215 * \text{Year} + -179.2952437) + 147392.5 * \text{Year} - 3 * 10^8$$

D. Summary and Verification of Model

We examined the yearly data for many climate related factors and then performed a multiple regression analysis for only the years that had complete data sets. A limitation of our data is that this complete set was only available for 2003-2011 in Acadia National Park. If expanded to other national parks, this would have a limiting factor of a small data set. After experimenting with parts of our dataset, we found out that the R^2 value varied significantly based on which years of data we used. After calculating the percent errors for every year of provided data, we concluded that our model is valid, seeing as all percent errors were less than 4%. This shows a considerably high correlation and validates our model. If given more time, we would have extended our model across all five national parks to have a more comprehensive model. We would have also incorporated more climate related sources and experimented with other models of regressions, such as quadratic or logarithmic.

Number of Visitors (Model)	2433383.61	2164907	2129430	2107793	2131230	2068909	2237913	2481922	2403129
Number of Visitors (Actual)	2,431,062	2,207,847	2,051,484	2,083,588	2,202,228	2,075,857	2,227,698	2,504,208	2,374,645
Percent Error	0.095497777	1.944901	3.799494	1.161713	3.223938	0.334683	0.458543	0.889932	1.199519

Figure 28: Verification of Model Using Percent Errors

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