Moody's Mega Math Challenge 2017

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From Sea to Shining Sea

Team 8873

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Executive Summary

In recent years, the National Park Service has faced increasing challenges in protecting its units from the effects of climate change and climate-related events. Modeling these events and mitigating their effects have become vital to modern park management.

We began by creating two models to predict sea level changes at 5 U.S. coastal parks—Acadia, Cape Hatteras, Kenai Fjords, Olympic, and Padre Island—over the next 10, 20, and 50 years. The first model uses the direct relationship between air temperature and sea level. The second forecasts park-specific sea level changes based on published global sea level projections. Both models yielded similar 10-year projections, but diverged over longer periods of time. We then assessed the amount of land lost at each park to determine that Cape Hatteras had the highest sea level risk rating, Acadia and Padre Island had medium risk, and Kenai Fjords and Olympic had low risk.

Next, we developed a weighted metric capable of assigning a climate vulnerability score (CVS) to any coastal unit based on 4 key factors: air temperatures, wildfire occurrence, hurricane occurrence, and sea level risk rating. We created individual metrics for the likelihood and severity of each, then combined them to determine the vulnerability scores for each park, shown in the table below. Higher values indicate higher vulnerability, so the lowest score is the best. Upon sensitivity analysis, our model proved to be extremely robust.

Park	CVS
Kenai Fjords	33.37
Acadia	51.25
Olympic	56.36
Padre Island	65.21
Cape Hatteras	121.97

Finally, we combined likelihood values from Part II with visitor statistics to create a model that predicts changes in the numbers of visitors in 2066 as a function of current visitation trends and climate change events.

Based on the NPS priority of preservation over recreation [9], we advise that the NPS give special climate change mitigation funding to parks with the highest climate vulnerability scores. Across the parks we analyzed, top climate change funding priority should be given to Cape Hatteras National Seashore. This funding could be used to move buildings inland to prevent damage from increased sea levels, rebuild or restore wildlife after natural disasters, or create infrastructure and marketing that attract visitors even as global temperatures rise.

As we proceed into the 21st century, climate change is certain to become a global challenge. Careful modeling, management, and mitigation is vital in order to preserve America's beauty from sea to shining sea.

Introduction

Tasked with managing and protecting all United States national parks, monuments, seashores, and other historical sites, the National Park Service (NPS) aims to preserve "unimpaired the natural and cultural resources and values of the National Park System for the enjoyment, education, and inspiration of this and future generations" [11]. As the NPS begins its second century of stewardship of our nation's ecological wonders, it faces new challenges in maintaining all units within the National Park system.

In recent years, climate change has emerged as a major concern for the NPS. Rising sea levels and other climate-related events threaten parks across the nation, particularly those along the coast. In this paper, we build several models to predict these climate-related phenomena in order to foresee risks and determine the most vulnerable parks. Specifically, we consider the following national parks: Acadia National Park (ME), Cape Hatteras National Seashore (NC), Kenai Fjords National Park (AK), Olympic National Park (WA), and Padre Island National Seashore (TX).

Climate change is likely to affect both park resources and visitor experience [11]. This paper provides the NPS with insights into the effects of climate change and how to best allocate resources among these five parks given the drastic changes in our global environment.

Part I: Tides of Change

1 Problem Restatement

One major impact of climate change is increasing sea levels. Rising global temperatures impact sea level in two major ways. First, increased temperatures cause glaciers to melt, thus releasing large amounts of water into global seas. Second, water density decreases as temperature increases (a phenomenon known as "thermal expansion"), meaning that the same amount of water will occupy a greater amount of space with higher temperatures [2]. The resulting sea level change can be especially devastating for coastal areas. Higher sea levels can destroy habitats, cause dangerous erosion, and contaminate soil [18].

2 Models

Modeling sea level change is vital. Predicting sea levels can help park managers prepare for and mitigate these effects. We predicted long-term changes in sea levels in two ways:

1. **Based on the correlation between temperature and sea level.** As explained in the previous paragraph, temperature and sea level are strongly correlated. Many models of sea level change use only temperature in their predictions (see Vermeer and Rahmstorf 2009, Grinsted et al. 2009). In this model, we determined the relationship between temperature data from the respective stations to the mean sea level. We then used this relationship between temperature and sea level to predict future sea level based on projected temperatures.

2. **By interpolating station-specific sea level changes based on global sea level changes.** In this model, we calculated the ratio of the sea level change at each station

to the global sea level change. We then used that ratio to interpolate station-specific sea level changes based on the 2013 sea level projections of the Intergovernmental Panel on Climate Change.

2.1 Temperature and Sea Level Model

2.1.1 Assumptions

- **Temperature has a roughly linear correlation with sea level.** This model relied heavily on the assumption that sea level has a linear correlation with sea level. It allows us to create linear regressions that accurately represent real-world data. The effects of higher air temperature primarily cause thermal expansion of seawater and cause the melting of polar ice shelves, both of which increase sea levels on a global scale.

- **Factors not directly related to temperature have a comparatively negligible effect on sea level.** Though other factors may affect sea level, this model considers only air temperature. Therefore, the effects of other short-term factors such as wave action, tidal motion, seasonal cycles, ENSO and PDO, as well as long-term factors such as plate tectonics are assumed to have a negligible effect on mean sea levels. Though many of these factors do cause variability on local, regional, and global scales, this model considers air temperature as the primary physical process affecting sea level.

2.1.2 Calculations

We supplemented the provided NPS temperature data at each site with NOAA data in order to provide more complete data [8]. We then constructed yearly average temperature plots, taking linear regressions of each. Our regression therefore is of the form

$$T = m_1 t + b_1,$$

where t is the year, T is the temperature, and m_1 is the yearly increase in temperature (in Fahrenheit).

We used additional data from NOAA to further complete our mean sea level data [12]. We then plotted our monthly mean sea level data against average annual temperatures to get a linear regression equation,

$$h = m_2 T + b_2,$$

where T is temperature (in Fahrenheit), h is mean sea level (in meters), and m_2 is the rate of increase in mean sea level relative to height.

Composing these functions then yields

$$h = m_1 m_2 t + m_2 b_1 + b_2.$$

We then use these equations to generate MSLs for each park 10, 20, 50, and 100 years after 2017. Graphs are available in the appendix.

Table 1: Projected Increase in MSL with Temperature (m)

Years past 2017	Acadia	Cape Hatteras	Kenai Fjords	Olympic	Padre Island
10	0.0361	0.0429	–0.0152	0.0416	0.0229
20	0.0434	0.0466	–0.0148	0.0672	0.0235
50	0.0652	0.0578	–0.0136	0.1439	0.0252
100	0.1016	0.0763	–0.0115	0.2719	0.0282

Using 2017 as our initial value, we can also interpret these values as a percent increase.

Table 2: Projected Percent Increase in MSL with Temperature

Years past 2017	Acadia	Cape Hatteras	Kenai Fjords	Olympic	Padre Island
10	22.4%	9.0%	2.7%	88.9%	2.6%
20	40.3%	17.3%	5.4%	123.1%	5.1%
50	77.4%	38.3%	14.1%	160.0%	12.3%
100	111.6%	64.2%	30.2%	177.8%	23.1%

2.1.3 Interpretation

This model allowed us to use data to calculate and predict the effects of temperature on sea level. We can observe low increases in MSL in both Cape Hatteras and Padre Island, with averages well under the maximum observed MSL 50 years in the future. Cape Hatteras's projection 50 years ahead also has an average well under its maximum experienced MSLs. Acadia's MSL is more troubling, with a 77.4% increase in MSL that begins to approach its most extreme. Paired with its high variance, this increased MSL could potentially cause flooding in later months. Olympic sees a great increase in this model, with an alarming 88.9% increase only 10 years into the future, and a massive 160% increase in MSL 50 years into the future.

This model had several strengths and weaknesses:

- **Strength: This model very easily provides results for times far into the future.** Because of its functional nature, this model is easily extended into the span of 100+ years and can easily be adapted to include new information as it comes.
- **Strength: This model accounts for the specific temperature data of each park.** By providing a regression model based on temperature data of each park, the model accounts for the local and regional differences between parks.
- **Weakness: Several months of data are missing from NOAA's data.** Though not significant enough to cause major inaccuracies, missing data leads to slight imprecision. More complete and thorough data would allow for this model to be more accurately representative of the real world.
- **Weakness: This model is naively linear.** Though accurate compared to other regression methods, a linear fit may not represent every aspect of the dynamic and changing sea levels. Its low R^2 values do not indicate a high correlation between time and temperature or temperature and MSL.

2.2 Global Sea Level Interpolation Model

This model used the historical proportion of local to global sea levels to interpolate local sea levels based on global projections.

2.2.1 Assumptions

- **Over time, local sea level changes are a constant percentage of global sea level changes.** A number of factors cause local sea level changes to deviate from the global mean sea level changes: land elevation, local currents, water salinity and temperature, and proximity to thinning ice sheets [4]. In order for local sea level changes to remain a fixed percentage of global sea level changes, the local values of these factors must remain the same with respect to the global values of these factors. This makes sense: for example, it is unlikely that the salinity of the water at a specific park will change differently from the average global salinity of the water, or that a park's proximity to thinning ice sheets will change.

- **The Intergovernmental Panel on Climate Change (IPCC) projections of sea level are reasonably accurate.** This model relied heavily on the IPCC's projections from their 2013 report [3]. The IPCC is the world's leading authority on climate change; as such, it seems reasonable to expect that their predictions are accurate [17].

- **A 15–20 year period is sufficient to realistically estimate the relationship between global and local sea level changes.** This model examined the period between either 1993–2015, 1993–2010, 1995–2015, or 1993–2013 (depending on location). Availability of data dictated the timing and length of the period.

2.2.2 Calculations

As mentioned in section 1.2.1, different time periods for each park were used to make projections based on the availability of data for that location.

This model took the form

$$\text{Projected LSL in year } n = \frac{\text{LSL over time period}}{\text{GSL over time period}} \cdot \text{Projected GSL in year } n, \qquad (1)$$

where LSL is local sea level and GSL is global sea level.

Using equation (1), we produced the following:

Table 3: LSL change relative to GSL change

Park and time period	LSL change (m)	GSL change (m)	Proportion of GSL change
Acadia (1993–2013)	0.04789	0.0557	0.85978
Cape Hatteras (1995–2015)	0.06242	0.0623	1.00192
Kenai Fjords (1993–2015)	–0.04855	0.06731	–0.72129
Olympic (1993–2015)	0.025909	0.06731	0.38492
Padre Island (1993–2010)	0.0355	0.045	0.78889

Table 4: Projections based on global sea level interpolation.

Park	10-year projected change (m)	20-year projected change (m)	50-year projected change (m)
Acadia	0.03448	0.07540	0.23515
Cape Hatteras	0.04018	0.08787	0.27403
Kenai Fjords	–0.02892	–0.06326	–0.19727
Olympic	0.01544	0.03376	0.10528
Padre Island	0.03163	0.06919	0.21576

Note that these projections are total, not cumulative—i.e., sea levels at Olympic National Park will have experienced a total increase of approximately 0.105 meters by 2057 rather than 0.015, 0.033, and 0.105 cumulative meter increases in 2027, 2047, and 2067, respectively. Since no IPCC projections were available for 2117, we did not include a 100-year projection.

2.2.3 Interpretation

This model allowed us to adjust global sea level increases to a local scale, illustrating how different locations are affected differently by global changes. We find that the Cape Hatteras, Acadia, and Padre Island parks will experience significantly larger increases in sea level over the next fifty years (20–30 centimeters) compared to the Olympic and Kenai Fjords parks. In fact, this model finds that the Kenai Fjords parks will actually experience a decrease in sea level, likely because the land in Kenai Fjords is consistently rising relative to sea level as nearby glaciers melt.

This model has a number of strengths and weaknesses.

- **Strength: This model allows us to determine the effect of climate change on specific parks.** By specifically isolating each park's LSL, this model focuses on the relative sea level of each individual park. This "micro" analysis is useful in determining different parks' relative risk, as we explore later in this section.

- **Strength: This model accounts for the systemic nature of changing sea levels.** It is self-evident that sea levels across the globe are interlinked; though the Acadia and Olympic National Parks might be geographically far from each other, they are both affected by the GSL. By using the IPCC estimates of GSL, this model incorporates system-level information rather than basing projections solely off local information.

- **Weakness: The necessary data for this model is only available for a limited number of years.** Historical GSL data is only available from the NOAA since 1993, and the IPCC predictions only extend to 2100. Since this model relies heavily on outside data, this lack of availability of a wide range of data restricts the scope of the model.

- **Weakness: The ratio LSL:GSL may not remain constant over extended lengths of time.** As explained in the Assumptions section, it is reasonable to assume that the LSL:GSL ratio is generally constant. However, over longer periods of time—say, a century or longer—it is possible that the LSL:GSL ratio could change. It is extremely difficult to foresee water conditions far into the future; major climate events may occur between now and 2117 that disrupt the ratio of LSL:GSL.

2.3 Analysis

2.3.1 Model comparison

Though both models generated different results, they ultimately both predicted that sea levels will change significantly in the next fifty years.

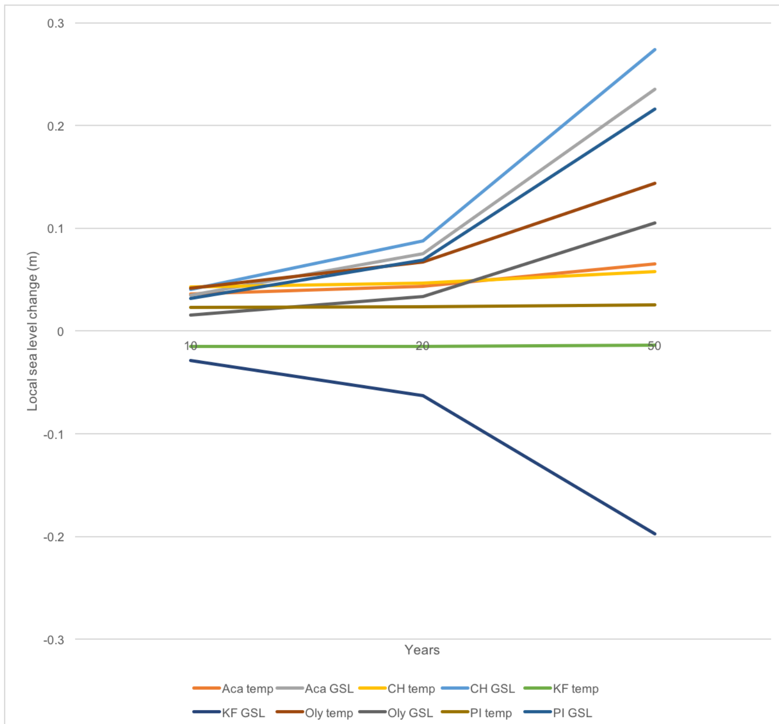

Figure 1: Projections of local sea level over fifty years by both temperature (temp) and global sea level interpolation (GSL) models.

Both models generally project a slower rate of increase for the first twenty years, then a more rapid divergence for the next thirty years (recall that both models are linear in form, so a line graph is appropriate). Interestingly, the temperature model projects increasing sea levels for the Kenai Fjords (KF) park, while the global sea level model projects decreasing sea levels. This is likely because the GSL model relies on current trends (which show Kenai Fjords' sea levels decreasing), while the temperature model attempts to generate future trends based on temperature projections and assumes a direct relationship between temperature and sea level—so if temperature is increasing, then sea levels must increase regardless of current trends.

Additionally, the models have generally similar predictions in the short (10-year) range, but tend to diverge in the long (50-year) range. Specific percent differences are shown below.

Table 5: Comparison of results from temperature and GSL models

Park	Projection range (years)	Temperature model projection (m)	GSL model projection (m)	Percent difference
Acadia	10	0.0361	0.0344	0.0459
	20	0.0434	0.0754	0.5387
	50	0.0652	0.2351	1.1317
Cape Hatteras	10	0.0429	0.0401	0.0655
	20	0.0466	0.0878	0.6138
	50	0.0578	0.2740	1.3033
Kenai Fjords	10	–0.0152	–0.0289	0.6219
	20	–0.0148	–0.0632	1.2416
	50	–0.0136	–0.1972	1.7420
Olympic	10	0.0416	0.0154	0.9173
	20	0.0672	0.0337	0.6624
	50	0.1439	0.1053	0.3099
Padre Islands	10	0.0229	0.0316	0.3202
	20	0.0235	0.0691	0.9858
	50	0.0252	0.2157	1.58

2.3.2 Risk Ratings

In order to best understand the risk associated with rising sea levels, we used both our mathematical models and a qualitative visual assessment of NOAA's Sea Level Rise Viewer [13]. For each park, we plugged our projected 50-year sea level increase into the viewer and evaluated how much land was flooded after that increase. Low ratings were assigned to parks that were almost entirely unaffected by sea level rises. Medium ratings were assigned to parks that are slightly affected, and high ratings were assigned to parks that were moderately to severely affected by an increase in MSL. We give the following ratings:

- **Acadia National Park: Medium.** Though its percentage increases may be high in the temperature model, an increase twice as large would still do little to affect the park land. Some significant changes may occur near Tremont in inclement weather, but even in the worst conditions, Acadia National Park will be relatively unaffected.

- **Cape Hatteras National Seashore: High.** Due to its location, Cape Hatteras is already in low-lying land. Combined with its comparatively high variance and steadily increasing averages, an MSL increase of even 0.3m could be high-impact.

- **Kenai Fjords National Park: Low.** Even a water level increase of 2 meters would not affect the Kenai Fjords. Neither of our models is near even 1 meter after 50–100 years.

- **Olympic National Park: Low.** Though a rising sea level may cause trouble for neighboring Olympia and Everett, Olympic National Park would not be directly affected by the predicted increases in MSL.

- **Padre Island National Seashore: Medium.** A 0.3m increase in MSL could cause major problems for Padre Island. Despite this, only one model shows an MSL increase close to this magnitude. Its high variance still causes it to be a concern.

2.3.3 Long-term predictive power

Temperature model: The temperature model relies on temperature forecasts, which are difficult to evaluate in the long term (especially given that human emissions can make a large difference in global temperature). However, our work and other literature show a consistent direct relationship between increased temperatures and rising sea levels. If we could accurately pinpoint future temperatures, then this relationship means that our model would likely be reasonably accurate in projecting future sea levels.

Global sea level model: The lack of IPCC sea level projections for the year 2117 automatically excludes this model from making 100-year projections. In addition, the assumption that the LSL:GSL ratio stays constant makes this model not ideal for long term projections.

Part II: The Coast Is Clear?

1 Problem Restatement

Rising sea levels are not the only climate-related event to threaten coastal park units. Factors such as increasing global temperatures and air quality also impact the climate of coastal areas. These factors can be investigated to better assess the likelihood and severity of extreme climate-related events. To better understand future climate conditions in the park, we developed a method of assigning climate vulnerability scores to any NPS coastal unit to help park managers protect local wildlife and preserve ecosystems. We also used provided data to predict the future occurrence of climate-related events, specifically hurricanes and wildfires.

2 Assumptions

It was necessary to make several new assumptions in this model:

- **The given historical data is accurate.** The data primarily used in the model is from highly reputable sources, including the National Park Service and the National Oceanic and Atmospheric Administration (NOAA).
- **The rates of natural, prescribed, and unplanned wildfires change together.** We do not distinguish between the three types of wildfires because of limited data. Instead, we quantify the impact of wildfires with a metric that describes how likely a wildfire is to spread and how much will burn, factors that affect the rates of all three types.
- **Vulnerability to hurricanes correlates with the storm's Saffir–Simpson category.** The Saffir–Simpson wind scale is one of the world's most widely used hurricane

scales. It rates hurricanes by wind speed and property damage. Since we wish to quantify how vulnerable each park is to hurricanes, i.e., how much destruction hurricanes will cause, the Saffir–Simpson scale is appropriate.

- **Parks with a high sea level risk rating are five times as vulnerable as those rated medium.** In our rating, medium indicates that sea levels changes are fairly low impact, while high indicates that the same change could have drastic or catastrophic effects on the park. Therefore, it is reasonable to assign a much higher vulnerability to the high rating than the medium rating.

3 Model

It is impossible to quantify every effect of climate change that might impact a park. In our model, we considered four of the most important events of each park's climate vulnerability: wildfires, hurricanes, extreme temperatures, and sea level changes.

3.1 Wildfires

Wildfires, planned or not, can completely reshape an environment. Uncontrolled wildfires destroy properties and unsettle ecosystems. To predict the future occurrence of wildfires in each national park for which data was provided, we assessed the fire potential of each national park using the Keetch–Bryan drought index (KBDI). This index represents the net effect of evapotranspiration and precipitation and relates to the flammability of organic ground material [6]. The KBDI yields a value ranging from 0 to 800, where 0 is indicative of high soil moisture and low likelihood of fire, and 800 is indicative of severe drought and high likelihood of fire. The following equation was used to calculate the KBDI for each coastal park:

$$KBDI = \frac{0.01(800 - Q)0.968^{0.0486R} - 8.3}{1 + 10.88^{-0.0441P}},$$

where Q is the moisture deficiency, R is the maximum temperature, and P is the mean annual precipitation.

We used the temperature projections in Part I and historical data to project KBDI values for each park. The KBDI values for 2017, projected KBDI values for 2066. Since the values were very close, their ratio was is not shown.

Table 6: Current and Projected Drought Index Values

Coastal Park	**Current KBDI (2017)**	**Projected KBDI (2066)**
Acadia	173.5	174.0
Cape Hatteras	228.3	229.0
Kenai Fjords	97.5	97.7
Olympic	350.4	351.4
Padre Island	167.6	168.1

High KDBI indicates a higher likelihood of wildfires and more intense fires. The trend for projected KBDI follows the trend of total wildfires in the given data; Kenai Fjords has the lowest KBDI and the least number of wildfires since 1997, while Olympic has the highest KBDI and experienced the most wildfires. We use the projected KBDI to represent vulnerability to wildfires.

3.2 Hurricanes

We assessed the frequency and intensity of hurricanes in only three of the five parks. Kenai Fjords and Olympic National Parks lie on the West Coast of the U.S. and are unlikely to ever experience a hurricane or storm of similar severity.

Hurricanes are most commonly categorized using the Saffir–Simpson scale, which is based on their peak wind speeds. The Saffir–Simpson scale gives us the following groups: tropical depression (TD), tropical storm (TS), Category 1 (H1), Category 2 (H2), Category 3 (H3), Category 4 (H4), and Category 5 (H5). In our model, we assign each of these categories a weight based on their intensity.

Table 7: Metric Weights for Each Hurricane Category

Saffir-Simpson Category	TD	TS	H1	H2	H3	H4	H5
Metric Weight	0	1	2	3	4	5	6

It's a common misconception that the warmer climate and increasing global temperature will lead to strictly more hurricanes in the future. However, the frequency of Atlantic hurricanes is not predicted to increase, and might actually decrease in future decades [1].

The same cannot be said for storm intensity, though. Scientists predict that low-intensity storms will decrease in frequency as more powerful—and damaging—hurricanes become more common in the warmer climates of the future. According to recent research, the frequency of H1 hurricanes and tropical depressions and storms will decrease by about 35%, the frequency of H2 and H3 hurricanes will decrease by about 30%, and the frequency of catastrophic H4 and H5 hurricanes will increase by 85% [1].

Using these numbers and the given data on hurricanes in the last two decades, we predicted how many of each type of storm would occur within the next 50 years (Table 8). We filled in "holes" in the hurricane data (unclassified storms) by examining maps of each storm's Saffir–Simpson rating along its path.

Table 8: Historical (gray) and predicted (white) number of storms per year

	TD		**TS**		**H1**		**H2**		**H4**	
Acadia	0.05	0.03	0.20	0.13	0	0	0	0	0	0
Cape Hatteras	0.25	0.16	0.80	0.52	0.25	0.16	0.30	0.21	0	0
Padre Island	0.05	0.03	0.3	0.20	0.05	0.03	0.05	0.04	0.05	0.09

Let F_x be the predicted yearly frequency storms that fall in the Saffir–Simpson category with metric weight x. For example, F_2 is the predicted frequency of H1 hurricanes.

Definition 1. *The **hurricane metric** of a park is*

$$H = \sum_{x=0}^{6} xF_x.$$

A park with $H = 0$ is predicted to have no storms heavier than a tropical depression, while a park with a high value of H will likely suffer heavy hurricane-related damages in the next 50 years. By default, $H = 0$ for Kenai Fjords and Olympic. We found that $\mathbf{H = 0.13}$ for Acadia, $\mathbf{H = 1.47}$ for Cape Hatteras, and $\mathbf{H = 0.85}$ for Padre Island.

3.3 Extreme Temperatures

One of the most well-known impacts of climate change is more intense weather. Extreme temperatures alone can cause highly damaging disruptions in the ecosystem, not to mention climate events that occur as a result of those extremes.

To quantify extreme temperatures in each park, we computed monthly and extreme "temperature deviations."

Let E_{max} and E_{min} denote a month's highest and lowest temperatures recorded, respectively. Let A_{max}, A_{avg}, and A_{min} denote the 30-year averages of that month's average maximum, average, and minimum temperatures, respectively. Finally, let T_{avg} be that month's average temperature.

Definition 2. *A month's* ***extreme temperature deviation*** *is*

$$E = 0.5((E_{max} - A_{max}) + (A_{min} - E_{min})).$$

Definition 3. *A month's* ***average temperature deviation*** *is*

$$A = |T_{avg} - A_{avg}|.$$

Note that A and E will always be positive. We used linear regression to find the trends in each park's temperature deviations over time (Figure 2), and used those equations to project future temperature deviations (Table 9).

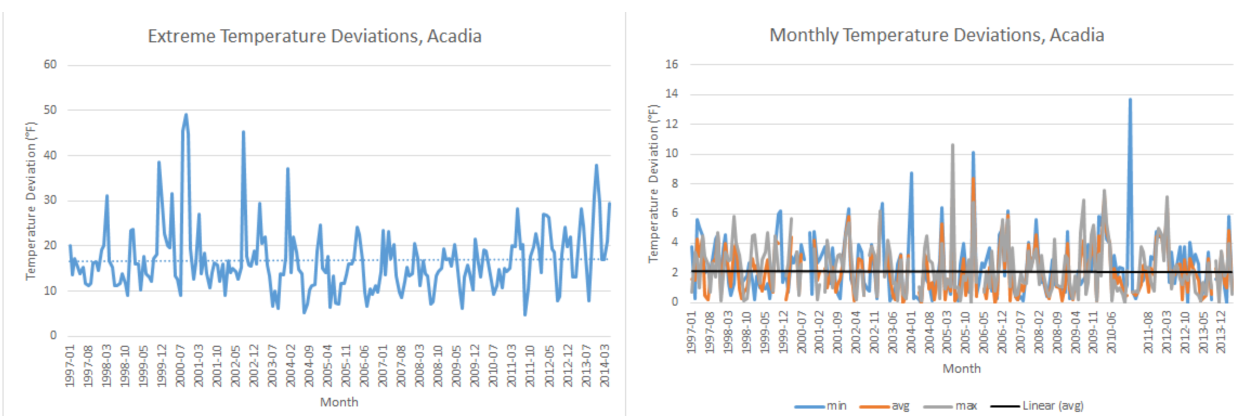

Figure 2: Example graphs for extreme (left) and average (right) temperature deviations

Table 9: Linear regression equations for temperature deviations

Park	Extreme	Average
Acadia	$y = 0.002x + 16.573$	$y = 0.001x + 2.2153$
Cape Hatteras	$y = 0.004x + 10.492$	$y = 0.005x + 1.615$
Kenai Fjords	$y = 0.004x + 15.002$	$y = 0.002x + 3.5536$
Olympic	$y = 0.0023x + 9.803$	$y = 0.006x + 4.6944$
Padre Island	$y = 0.002x + 8.4111$	$y = 0.006x + 5.5588$

Table 10 shows the calculated projections for December 2066, or 50 years from January 2017. Both average temperatures and the especially severe extreme temperature deviations are impactful on a park's ecosystem, so we combined both by adding the two deviations to find T, the total temperature deviation.

Table 10: Projected temperature deviations for 50 years into the future

Park	Extreme (°F)	Average (°F)	Total (°F)
Acadia	18.25	3.00	21.25
Cape Hatteras	13.85	5.82	19.67
Kenai Fjords	18.36	5.23	23.60
Olympic	11.48	9.73	21.22
Padre Island	10.80	10.60	21.40

It is interesting to note that all five parks had fairly close values of T, reflecting how far-reaching the global trend in temperature is.

3.4 Sea Level

In Part I, we evaluated the sea level change risks of each park and how vulnerable each location is to changes in sea level. Sea level changes are important to consider for overall climate vulnerability as well, since these coastal areas feel the effects most strongly. We quantified sea level risk ratings to a single variable, S, by setting $S = 0$ for low risk, $S = 10$ for medium, and $S = 50$ for high.

3.5 Combined Metric

Our goal was to quantify climate vulnerability in each park by combining the previously discussed factors into a single metric. We did this by computing a weighted sum of all calculated values. The weights were chosen in order to scale each factor similarly, so that the combined metric would not be much more or less sensitive to a single factor.

Definition 4. *The* ***climate vulnerability score*** *of a park is*

$$CVS = 0.1KBDI + 20H + T + S.$$

A park with $CVS = 0$ has no vulnerability; it is not predicted to experience any hurricanes, wildfires, or other climate-related events. The climate vulnerability scores of each park are listed below:

Table 11: Climate vulnerability scores for each park

Park	CVS
Acadia	51.15
Cape Hatteras	121.97
Kenai Fjords	33.37
Olympic	56.36
Padre Island	65.21

Our CVS metric yielded results that are similar to what we expected. It makes sense that Kenai Fjords is the least vulnerable park since it's located in Alaska, where it is safe from hurricanes, too cold for wildfires, and at low risk of sea level change. Conversely, Cape Hatteras scored the highest, indicating it has high vulnerability. Intuitively, it's in an ideal location and climate for hurricanes, wildfires, and drastic sea level changes.

4 Analysis

4.1 Sensitivity Analysis

It is important that our model show high tolerance for variance in the inputs or assumptions. We made several changes in our data to check how resulting metrics would vary.

The values of KDBI were extremely robust. Positive and negative changes of 100% in Q and R resulted in less than 4% differences in the value of projected KBDI for every park, and doubling P had a similar effect (less than 5% change). As a result, there was little change in CVS or overall vulnerability ranking of each park.

We also tested the effect of varying hurricane frequencies. Changing any projected frequency by up to 0.05 changed the final CVS values by less than 15% for every park, and only an increase in H5 frequency for Acadia resulted in any change in CVS rankings.

Doubling any of the linear regression slopes used for temperature deviation resulted in a maximum change of approximately 23% in T. Other factors in the CVS further reduced the sensitivity, to a maximum 15% change in the CVS of any park.

Varying the sea level values did have a noticeable impact on each park's CVS, since any change in S is directly a change in CVS. However, overall vulnerability rankings of the parks was unchanged as long as medium and low risk values differed by more than 18. Given the scale of our metric, this would be highly unwise and unlikely.

4.2 Strengths and Weaknesses

This model had a number of strengths and weaknesses:

- **Strength: Our models are heavily based on highly accurate historical data.** Our projections of wildfire occurrence, hurricane occurrence, temperature, and sea level closely reflect the trends present in the past 20 years of data.

- **Strength: Sensitivity testing shows that our metric is highly robust.**

- **Strength: Our metric considered both the likelihood and severity of several climate-related events.** In addition to the frequency of climate-related events, hurricane category, wildfire spread potential, extreme temperatures, and the risk posed by rising sea levels were also included in our model.

- **Strength: Our model can easily be extended.** Given appropriate data, each metric can be easily calculated for any other national park or coastal region. This allows the NPS to easily extend our results to the rest of the park system if needed.

- **Weakness: Predicted hurricane frequencies are based only on the given historical data.** Our model depended on past occurrences to predict future hurricanes. For example, we could not predict the frequency of any Category 3 or 5 hurricanes because none occurred at the specified coastal parks during the previous 20 years.

- **Weakness: Our model did not completely consider every possible climate change factor.** It is difficult, if not impossible, for us to account for every factor. With more time and resources, we would like to explore more factors.

Part III: Let Nature Take Its Course?

1 Problem Restatement

Like any governmental agency, the NPS has a limited budget that must be split among its many units. In this section, we investigate how the NPS ought to allocate funds based on projected changes in visitor numbers. We combined metrics described in Part II with the provided visitor data to generate projected changes in numbers of visitors. Instead of using only the CVS itself, we used each component of the metric in order to maximize accuracy.

2 Assumptions

- **Changes in number of visitors can be accounted for by two variables: existing trends in visitation, and uncommon outside events.** Our model includes two types of variables. The first accounts for trends in visitation seen in the provided NPS visitors data, and the second type accounts for climate-related events. We assume that visitation would not vary from existing trends until disturbed by some outside event.

- **Outside events solely take the form of natural disasters.** In reality, events like wars, disease outbreak, and economic downturn can all affect park visitation. However, modeling such events is beyond the scope of this paper. We restrict our model to the consideration of climate-related events like hurricanes or wildfires.

- **Barring outside events, the changes in numbers of visitors can be effectively modeled with a linear regression.** Like any real-world data, the visitor numbers from the NPS visitors data do not conform perfectly to a specific equation, so some kind of assumption regarding regression type must be made. Based on the lack of compelling evidence for any specific type of regression (e.g., quadratic, exponential, logarithmic, etc.), we assume that trends in visitor data can be reasonably approximated with a simple linear regression.

- **Parks with a Keetch–Bryan drought index (KBDI) value of 800 are guaranteed to experience a wildfire during that year.** 800 is the maximum value that KBDI can take, representing absolutely dry conditions. Especially considering that wildfires are relatively common (on average, there are over 100,000 wildfires per year [10]), it can be logically assumed that a wildfire would definitely occur under such dry conditions.

- **A wildfire will close a park for 3 days.** We assume that wildfires will close the park for a short amount of time. Considering that wildfires are so common and generally do not affect park infrastructure, we assume that parks will only be closed for a short amount of time after a wildfire.

- **Hurricanes affect every park in the same way: closing it for a specific number of weeks.** Hurricane damage is notoriously difficult to predict, so we make an assumption that parks will close when hit by a hurricane for a specific number of weeks. A Category 5 hurricane will close a park for 6 weeks, a Category 4 for 5, a Category 3 for 4, and so on.

- **Fewer visitors come to parks when temperatures are more extreme.** If temperatures are significantly different from average temperatures, fewer visitors will come to the parks.

3 Model

3.1 Notation

In this model, we considered the total number of visitors to a particular park per year (denoted by V_t) and our projected number of visitors per year based on historical data (denoted by V_p). We utilize the following parameters in our model:

K represents the probability of a wildfire in the year 2066, which we calculate as

$$K = \frac{\text{KBDI}}{800}.$$

Recall that a KBDI score of 800 is the extreme, absolute dry value.

F_x, as explained in Section 3.2, represents the probability (in the year 2066) of storms that fall in the Saffir–Simpson category weighted in our metric with a weight of x (recall that Category 5 hurricanes have an x of 6, Category 4 have $x = 5$, Category 3 have $x = 4$, etc.).

T is defined as the number of degrees that average temperature over the year 2066 differs from average yearly temperature. We estimate from personal experience that every 10°F difference corresponds with a 40% reduction in visitors.

S represents risk (low, medium, or high, as described in Part I) that a park will be damaged by an influx of water after an increase in sea level. High risk parks have an S of 0.3, medium parks have an S of 0.1, and low risk parks have an S of 0.

Each disaster was associated with an annual probability of occurrence and closure time. Note that each closure is associated with the loss of a specific number of visitors. This formula used this probability and closure time to generate an expected value in terms of visitors lost because of that particular disaster.

Ultimately, we find that

$$V_t = (1 - S)(0.6^{\frac{T}{10}}) \left(V_p - K\frac{3V_p}{365} - \sum_{x=0}^{6} F_x \left(\frac{V_p}{365} \cdot 7x \right) \right). \tag{2}$$

3.1.1 Evaluation

Evaluating the above equation for the values in 2066, we produced the following V_t values for each park. We also calculated the percentage lost, which is the percent difference between V_p and V_t.

Table 12: Projected visitor numbers for each park in 2066.

Park	2016	2066	% Lost
Acadia	3,303,393	2,200,135	23.12
Kenai Fjords	346,534	610,270	23.52
Olympic	3,390,221	2,561,969	40.35
Padre Island	634,012	257,933	47.72
Cape Hatteras	2,411,711	1,994,111	49.59

3.1.2 NPS recommendations

The NPS Chief of Public Affairs states that "when [the NPS has] to make a choice between recreation and preservation, we will always choose preservation"[9]. As such, we advise the NPS to provide the most funding to parks with the highest climate vulnerability scores (CVSs). Of course, funding from entrance fees is vital for the NPS, earning them hundreds of millions of dollars every year[15]. As such, the NPS should also provide additional funding to parks projected to lose more of their visitors over the next fifty years.

In our analysis, the park with both the highest CVS and percentage of visitors lost is Cape Hatteras National Seashore. Additional funding to Cape Hatteras could go towards shoring up the park against damage from increasing sea levels (moving buildings upwards or inland), protecting against storm damage, or an emergency fund that goes towards reconstructing infrastructure after storm or wildfire damage.

4 Strengths and Weaknesses

This model had several major strengths and weaknesses:

- **Strength: The model creates specific estimates for visitors in a particular year.** The model outputs a specific number of visitors to a particular park in one year, not just a rank or probability. This kind of specific figure could be very useful to park managers in their long-range planning processes, and to the NPS for budgeting purposes.

- **Strength: The model accounts for many natural disasters, as well as existing visitor trends.** The model accounts for wildfires, storms, sea level changes, and extreme temperatures, which cumulatively account for 38% of natural disasters worldwide [7].

- **Weakness: The park closure parameters in the model are based on very specific assumptions.** For example, we assume that a Category 5 hurricane will close a park for 6 weeks, that a wildfire will close a park for 3 days, etc. Since natural disasters and their effects are so inherently unpredictable, it is difficult to determine the precise effects of a particular disaster on a park; at some point, approximate values must be assumed for these park closure parameters. Greater precision in these parameters would likely lead to a more accurate model.

- **Weakness: The probabilities of disaster incorporated in the model are difficult to approximate.** In Section II, we approximated hurricane probabilities in the year 2066; we also converted the drought index to a measure of wildfire probability. These probabilities are not precise and likely contain a significant amount of error. Of course, natural disasters are very difficult to model, and determining precise probabilities is beyond the scope of this paper.

5 Future Work

This model could be further strengthened by:

- **Varying parameters.** Our assumptions regarding the length of park closure could be varied to further increase robustness.

- **Incorporating seasonal variation.** The current model assumes that there is an equal likelihood of a particular natural disaster over the entire year.

- **Evaluating the model for years other than 2066.** A lack of time prevented us from completing calculations for this model for other years. However, the process for completing calculations is described in our paper and could easily (with additional time) be completed for earlier or later years.

- **Expanding the model to account for more types of natural disasters.** Additional natural disaster probabilities, along with their corresponding closure times, could be added to the model in ways similar to the ways that hurricanes, wildfires, and sea level change are incorporated.

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