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2017: "Park2Vec: A Vector Representation of Our National Parks' Climate Change Susceptibility"

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Summary | Team #9403

With over 400 units, between them covering almost 850 million acres of carefully preserved land, the National Park Service (NPS) acts as steward to the nation's natural treasures. In the move to the Twenty-First century, the NPS faces numerous looming challenges, particularly those related to a rapidly changing climate. It was our task to strategize with the Service in addressing three such issues, leveraging our experience in mathematical modelling and data analysis to aid them in the quest to protect and to preserve.

The first problem under consideration was determining the risk associated with sea-level change for five different coastal locations. Risk was categorized as being "low," "medium," and "high" over a period of 10, 20, and 50 years. The lines between the three intensities were determined by the intermediate-low and intermediate-high predictions of global sea-level rise, as given by the National Oceanic and Atmospheric Administration (NOAA). For example, if a location's predicted rise in sea-level fell below the intermediate-low prediction for the rise in global sea-levels, it was deemed a "low" risk. If it fell in the middle, a "medium" risk. And above the intermediate-high line, a "high risk." Together with other considerations like the elevation of a park, the final valuations are presented on page 8. Given the nature of the model and the inherent unpredictability of climatology, the model cannot be extrapolated to 100 years, but works fairly well in the given time frame.

The next challenge involved assigning climate vulnerability scores to coastal locations based on the susceptibility of each location to natural disasters. Such scores were determined as a product of the severity of a particular disaster with its frequency. By plumbing datasets provided, vulnerability scores for each of the five locations under analysis were determined and are presented on page 13.

The final task sought to determine where the NPS's financial resources should go based on the value of each park. By leveraging the vector-like nature of the vulnerability scores along with the popularity of each location and sea-level rise considerations, a graphical model was generated grouping parks of higher and lower values together in a distinguishable manner, as presented on page 16. From this graphic, our final recommendation to the NPS would be, in times of tight revenues, to fund Olympic National Park, consider funding Acadia and Kenai Fjords, and avoid funding the seashore locations.

Park2Vec: A Vector Representation of Our National Parks' Climate Change Susceptibility

Team #9403

February 26

1 Introduction

For the past 100 years, the National Park Service (NPS) has maintained the nation's natural treasures for both the sake of ecological preservation and general recreation. Transitioning into another century of stewardship, the NPS faces a plethora of new challenges, particularly in the domains of climate change and climate-related catastrophes [3, 4].

In this study, we sought to explore the impact climate may have on five specific NPS locations:

- Acadia National Park
- Cape Hattaras National Park
- Kenai Fjords National Park
- Olympic National Park
- Padre Island National Park

For each location, a number of specific issues were considered. In Part 1, we analyzed the impact rising sea-levels would have on each location and assigned the parks corresponding risk ratings. In Part 2, we expanded our analysis by considering all potential natural catastrophes for any NPS coastal unit, and applied our methods to derive climate vulnerability scores for the five locations. And finally, in Part 3, we factor in financial variables by considering long-term changes in tourists to each park, and make corresponding recommendations on where NPS's future financial resources should go.

2 Part 1: Tides of Change

2.1 Restatement of Problem

In order to take a first step in modeling climate data, we were first tasked with extrapolating existing sea level data in order to predict sea level change risks for five different parks. For each of these parks (listed above), we were asked to determine whether the risk was high, medium, or low. To accomplish this, we used a well-accepted quadratic model based on empirical observations [7].

2.2 Assumptions and Justifications

- **Assumption:** The equation presented in this paper [7] written as $E(t) = at + bt^2$ is an accurate approximation of long-term sea level rise. t is defined as time in years, and begins with year 0 at 1992. a is a constant defined as the rate at which global sea level rises, accepted as 0.0017 meters per year on a global scale. b is a constant derived empirically from the data, encapsulating local factors like continental uplift/subsidence and water density.

  Justification: The paper is highly cited and this equation is used multiple times in other papers suggesting it is a widely accepted equation.

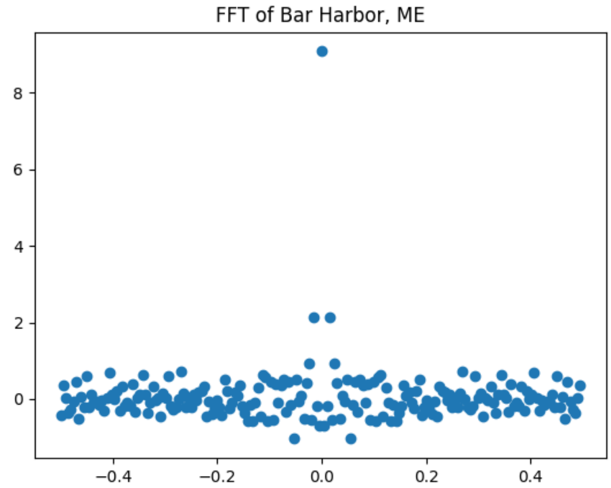
- **Assumption:** Climate change data is nearly completely stochastic except with respect to a quadratic function.

  Justification: After performing a Fourier transform on the data, we determined that there was no periodicity associated with the data.

2.3 Model

2.3.1 Fourier Transform

The data given for the MSL (Mean Sea Level) was clearly stochastic in nature. A common practice in signal processing when looking at data of this sort is to apply a Fourier Transform on it to determine if there are any frequencies that are more common than others. Viewing such signals in frequency space is often more revealing of internal structure allowing for a seemingly indescribable mathematical function to be nicely encapsulated in a more fitting space. This led us to applying the Fourier transform on our MSL data which could have potentially given us information on seasonal trends or underlying periodicity. We used the data for all of the cities to calculate the fast fourier transform and look for patterns. A graph of the fourier transform is shown below:



Upon calculation, it was revealed that, other than the center point, there were no clear peaks in frequency. The center peak, which represents the amplitude of 0 frequency, is merely a calculation of average value and yields no significance in showing periodic trends in the data. All other frequencies occurred with similar amplitude which implies a white noise signal. White noise signals are essentially random. This does not mean there is no structure in the data but that there is no clear periodicity. From this, we were able to conclude that the data might require an approximation method that is not based on periodicity like perhaps a polynomial one.

2.3.2 Quadratic Regression Analysis

After determining that the data was not periodic, we decided to do a simple quadratic regression analysis in order to plot how MSL rates were changing over time. The reason for this is an algorithm found in [7] that uses a quadratic regression to model climate data over time. The algorithm uses a quadratic equation of form $at + bt^2$ where month "0" is set to be January 1997. To do this, we simply employed a "curve of best fit" to our given data. Doing so yielded the following tables of equations where time is given in years and the sea level is given in meters.

City	Equation (m)
Acadia	$(2.18 \times 10^{-3})t + (1.09 \times 10^{-4})t^2$
Cape Hattras	$(3.84 \times 10^{-3})t + (1.61 \times 10^{-4})t^2$
Kenai Fjords	$(-2.62 \times 10^{-3})t + (-1.60 \times 10^{-4})t^2$
Olympic	$(1.4 \times 10^{-4})t + (2.56 \times 10^{-5})t^2$
Padre Island	$(3.48 \times 10^{-3})t + (-4.70 \times 10^{-5})t^2$

2.3.3 Defining Low, Medium, and High

In order to define the somewhat arbitrary terms “low”, “medium”, and “high”, we utilized a paper that presented four different quadratic regression models of climate data. These models were presented to model for worst-case, best-case, intermediate-low, and intermediate-high scenarios of global climate change (shown below).

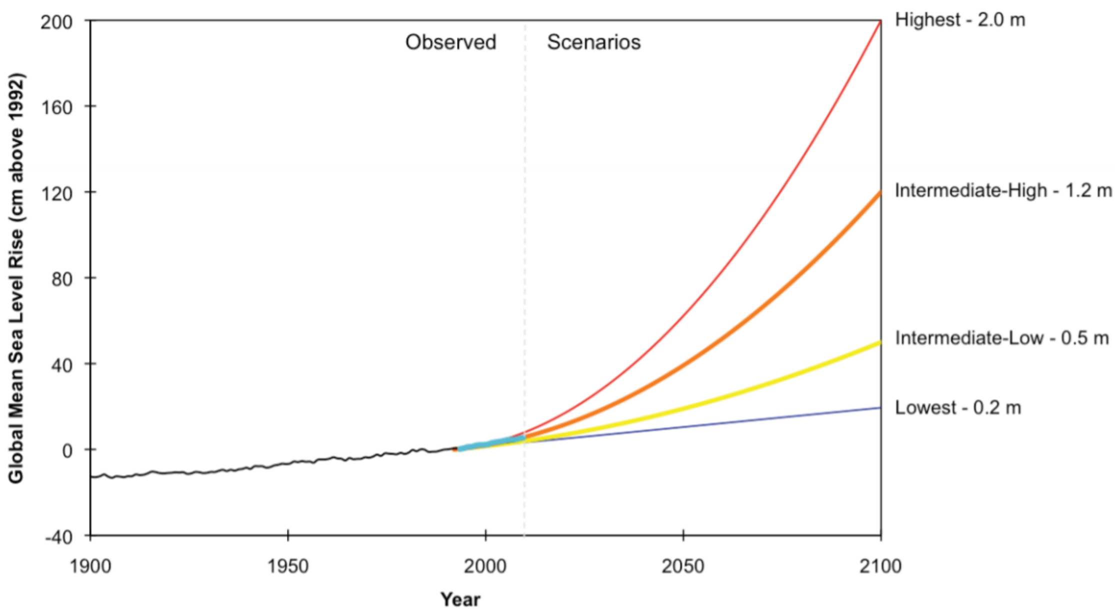


Figure 1: Fig 1. A predictive measure of global climate change rise from 1900 to 2100. Utilizes four scenarios to measure climate change rise.

Due to this we decided to utilize this global data as benchmarks to measure our local data. For our model, a high risk area would mean that the estimated sea level rise is greater than the intermediate-high calculated value for global climate change. A medium risk area, on the other hand, would mean that the estimated sea level rise falls in between the intermediate-high and intermediate-low curves. Finally, a low risk area falls below the intermediate-low curve.

These equations, however, were calculated assuming that the year 1992 as 0 for sea level. Therefore, we must adjust the calculations to account for our 1997 as our 0 value.

The equations for the two curves are given as follows:

$$\textbf{Intermediate-Low: } E = (1.7\times10^{-3})t + (2.71\times10^{-5})t^2 - 9.178\times10^{-3} \quad (1)$$

$$\textbf{Intermediate-High: } E = (1.7 \times 10^{-3})t + (8.71 \times 10^{-5})t^2 - 1.07 \times 10^{-2} \quad (2)$$

2.4 Results

Now that we have established all of the curves, we can go ahead and compare the results. Simply plugging in values of 30, 40, and 55, accounting for the difference from 1997 to the desired years of 2027, 2037, and 2057, we can obtain our results. The corresponding graphs for each city are shown. The dashed orange line represents the quadratically extrapolated line from the data and the green region represents the medium zone. All points higher represent high sea level rise and all points below represent low sea level rise.

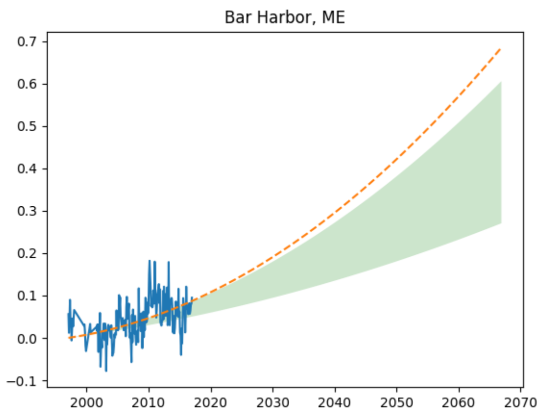


Figure 2: Graph of projected sea levels for Acadia National Park

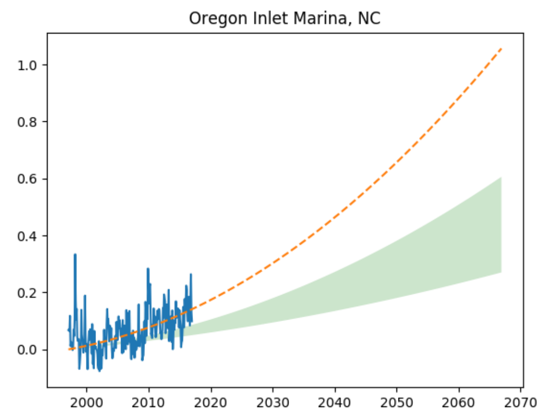


Figure 3: Graph of projected sea levels for Cape Hattras National Park

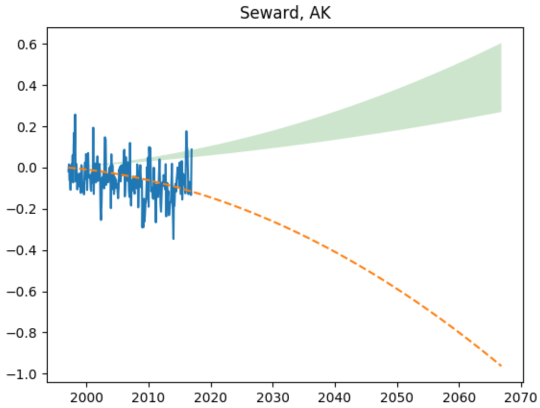


Figure 4: Graph of projected sea levels for Kenai Fjords National Park

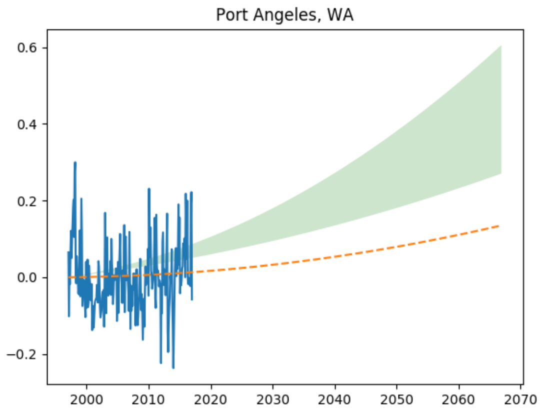


Figure 5: Graph of prjected sea levels for Olympic National Park

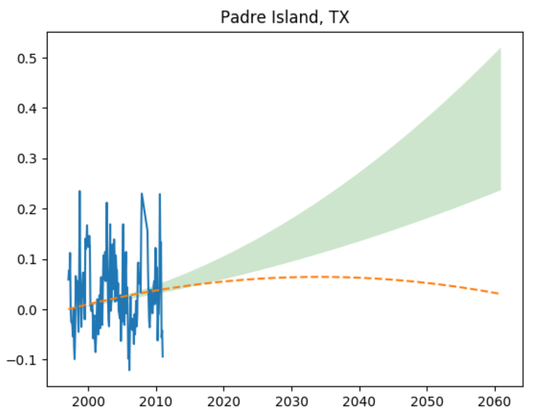


Figure 6: Graph of prjected sea levels for Padre Island National Park

From this data, we can gather our final assessments of climate risk.

National Park	10 Years	20 Years	50 Years
Acadia	LOW-MED	LOW-MED	LOW-MED
Cape Hattras	HIGH	HIGH	HIGH
Kenai Fjords	LOW	LOW	LOW
Olympic	LOW	LOW	LOW
Padre Island	MED	MED	MED

2.5 Analysis and Discussion

First off, in determining the final valuation of "low". "medium", or "high", it is vital to consider the elevation at each location. For example, while Acadia may have had a projection higher than the intermediate-high level, it is a fairly mountanious region. A rise in sea level of a meter would therefore do little to damage the park, thus earning the place a low-medium rating. Overall, it was found that Acadia and Kenai Fjords tended to be fairly mountainous regions with high elevations, Cape Hattras and Padre Islands were seashores with correspondingly low elevations, and the Olympic National Park had both seashores and mountains.

Interestingly, while global sea level tends to rise, it appears that the sea-level is, in fact, falling for certain locations. Such a result may be due to a phenomenon called "continental uplift," in which a landmass floats upwards on the mantle after the weight of a glacier has been lifted. For example, Alaska is currently experiencing uplift, increasing the volume of the basin holding surrounding water and thus, causing the sea level to dip [2]. Of course, it is important to note, the equations used to project future behavior of sea-levels are not designed to except values describing decreasing sea-levels (i.e. a negative b), so the long-term trends in these plots are likely inaccurate.

In the case of Padre Island, the inaccuracy is the long-term trend is especially evident. Given its lower elevation and the rate of global sea-level rise, it is likely Padre Island will be somewhat submerged within the next half century, despite having a relatively gentle curve [11]. Thus, it was given the rating of "medium" across all three time intervals.

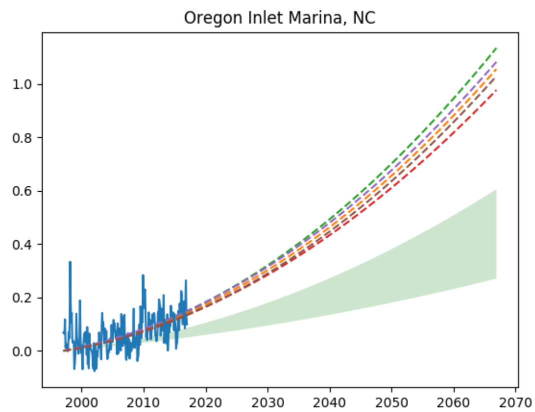
Finally, in considering whether the model may realistically predict sea levels one hundred years into the future, the answer would be a resounding "no." Any extrapolation to such a dramatic distance, especially in a field as fickle as climatology, is a risky enterprise. Furthermore, as already demonstrated with Padre Island, locations with a dropping sea level cannot be accurately modelled too far into the future with the present model. And finally, the quadratic equation itself central to the analysis is merely and empirical approximation with minimal theoretical basis. No future trends can be expected to be as smooth as it predicts [7].

2.5.1 Sensitivity Analysis

In order to do sensitivity analysis, we will look into only Cape Hattras national park. Had we had more time, we would like to do sensitivity analysis on each of the parks. To test sensitivity, we will change the values of the coefficients of the t and t^2 term on the Cape Hattras equation. A table of values is shown below. In the table the coefficient of the t term is denoted a while the coefficient of the t^2 term is denoted b.

a % Change	b % Change	10yr % Diff	20yr % Diff	50yr % Diff
10%	0%	5.57%	6.26%	7.45%
-10%	0%	-5.57%	-6.26%	-7.45%
0%	10%	4.42%	3.73%	2.54%
0%	-10%	-4.42%	-3.73%	-2.54%

As one can see, a percent change of 10% amounted to a change less than 10% in the data. Therefore, we can say our model is robust. A graph of the percent differences is provided below:



2.5.2 Strengths

- Alignment with the literature - The model used to predict the behavior of sea levels for each of these national parks matches those used to model sea levels on a global scale. Although this regression may seem questionable as a descriptive model for a complex behavior like sea level change, it is very well supported empirically in the literature of the field.

- Simplistic and generalizable - The model provides an approach that can be universally applied to any site in a very simplistic manner. It does not require extensive simulation or computational rigor.

2.5.3 Weaknesses

- Lack of scientific basis - The approximation, although descriptive, is unjustified on a scientific basis which is a fact acknowledged by the original paper itself. It is a purely empirical formula. Perhaps, a better model would have been to find a stochastic way to simulate and extrapolate future data points. A common process for doing so, especially in predicting the market, is using Wiener processes and the following differential equation as described in [5].

$$\mathrm{d}X = a(X,t)\mathrm{d}t + b(X,t)\mathrm{d}W_x$$

where X is the measured variable, $a(X,t)$ is some base function, $b(X,t)$ is the stochastic factor, and $\mathrm{d}W_x$ is a Wiener process or, put more simply, a random Gaussian value. By using an accepted function for $a(X,t)$ like the aforementioned quadratic and running a Monte-Carlo simulation to extrapolate a $b(X,t)$ for the data, it may have been possible to run a more accurate stochastic simulation of the future sea level.

3 Part 2: The Coast is Clear?

3.1 Assumptions and Justifications

- **Assumption 1:** Vulnerability is better described as a vector of values for different climatic events rather than a single encompassing value

  Justification: Often times, the effect of events such as wildfires or hurricanes have different effects on different sites. A small hurricane may be significantly more detrmental to a site than multiple wildfires. As a result, creating a way to calculate vulnerability for a general site would ignore such differences and would thusly not be a holistic representation of vulnerability.

- **Assumption 2:** Vulnerability can be expressed as a product of severity and frequency.

  Justification: Severity can be measured as the average magnitude of an event and frequency as the average number of events per unit of team, yielding a product that represents the sum magnitude across all events per unit of time

3.1.1 Model

Perhaps the biggest obstacle facing this section of the analysis was finding an effective way to generalize climate catastrophes across the massive diversity of types and contexts. To accomplish this feat, we approached the model using a two-part strategy.

The first part consisted of forming a general framework applicable to any park in any climate susceptible to any natural disaster. The two variables forming a "climate vulnerability score" were given as severity and frequency of a particular kind of disaster. To extract a score, the two components were simply multiplied. In this way, if severity can be defined as a measure of damage wrought per natural disaster event, and frequency can be defined as a measure of events per unit of time, then a simple multiplication of the two factors yields a measure of damage wrought per unit of time. Because of the ultimate goal of a climate vulnerability score is to determine the susceptibility of a location to climate catastrophes, such a general framework was determined to be a simple, clean approach to calculating such a score.

The second part consisted of adapting the general framework to the specifics of each, individual location. First off, it became evident that translating a particular severity in one variety of natural disaster to another was highly dependent on context and therefore an unproductive approach. For example, consider equating severity in a forest fire to that of a hurricane. For in a location like a forest preserve, a relatively small forest fire may be considered as devastating as a fairly powerful hurricane, whereas in a coastal park, a relatively relatively mild hurricane may be considered even worse than a moderate forest fire. Therefore, our model sought to keep individual scores for each variety of natural disaster separated. Instead of calculating a grand vulnerability score encompassing every possible catastrophe, we instead produced a data structure analogous to a vector, extracting a vulnerability score based on the framework outlined in the previous paragraph for each variety of natural disaster under consideration. To do so, data was pulled directly from the data-sets provided. Below is a list of the natural disasters considered along with a description of how they were evaluated:

- Hurricanes
  - Severity of hurricanes was judged by their wind-speed. The average wind-speed for each hurricane at a location was multiplied by the average number of hurricanes expected per year, giving an estimate for the total wind-speed of hurricanes at a location per year.
- Forest fires
  - Severity of forest fires was judged by the area of land damaged, measured in acres. Much opportunity for more delicate analysis was provided in the data-set with measurements like ecological damage, but acre was chosen

simply in the interest of time. The average acreage damaged per each fire was multiplied by the average number of forest fires per year, yielding the average acreage damaged by forest fires per year.

- Extreme low temperatures
  - Temperatures were measured using the distance (in standard deviations) from the mean at a particular measurement station. Such an approach was favored over using the exact temperatures themselves in order to more rigorously compare temperatures across locations of different climate (for example, -10 degrees F will mean different things in Alaska as compared to Texas). In this case, means and standard deviations typical to a measurement station were obtained from the National Oceanic and Atmospheric (NOAA) Administrations' Global Summary of the Month (GSOM) data-sets. Z-scores for each month's record low of each year were calculated against the averages to obtain a severity. Methodology like that described above was performed on these severeties, yielding the average number of standard deviations below the average in temperature per year. The Z-scores are signed, so a final vulnerability of score of -50 would mean a total of 50 standard deviations below normal observed in temperatures in an average year at that location.
- Extreme high temperatures
  - The methodology detailed above was repeated with high temperatures, replacing the record low's for each month with record high's.
- Air quality
  - Severity of air quality was determined with the Air Quality Index (AQI). The average AQI at each location per month was multiplied by the number of months per year, giving the average sum AQI over a typical year.

3.2 Results

Below are the vulnerability score "vectors" for each location.

National Park	Hurricane	Forest fire	Temp (Low)	Temp (High)	Air quality
Acadia (ME)	27.8	10.6	-75.1	58.9	41.5
Cape Hatteras (NC)	116	18.1	-13.2	37.3	43.2
Kenai Fjords (AK)	0	0	-70.5	7.49	31.8
Olympic (WA)	0	576	-31.3	23.8	35.5
Padre Island (TX)	37.1	2420	2.23	32.7	44.6

3.3 Analysis

Reassuringly, the vulnerability scores appear to corroborate a general understanding of each location. For example, the Kenai Fjords in Alasksa, a state in the far north, have a remarkably negative low-temperature score and an accompanying small high-temperature score, supporting the notion that the area produces days of incredible chill.

3.3.1 Strengths

This model leverages simplicity in that a general framework with universal applicability is applied on a case-by-base basis to produce specific results for a particular location. In this way, the model ceases to be so much a model as a methodology for constructing models for various park locations. Furthermore, the simple framework leaves plenty of space for flexibility. If one would like to take into consideration other natural disasters like drought or tornadoes, these elements may be added on as simply as an item being appended to a list, with severity measured in no unit more complex than the units traditionally used to gauge the disaster.

Additionally, another strength of our model is our adaptability towards cost. If a park would wish to determine a single vulnerability score, they may simply dot the vector representing their vulnerability scores with the amount they wish to spend on each natural distaster. We would have done this ourselves given more time.

3.3.2 Weaknesses

In our specific case, there is much more opportunity to further define the severity of the forest fires. While acreage is a fine representation, an acre burned in a wilderland would be far less catastrophic than an acre burned in the Enchanted Groves of Lothlorien, stocked with all sorts of rare plants and endangered species (and High Elves). Thus, taking into account other factors like ecological damage would be an important imporvement on the current estimation of a forest fire's severity. Given more time, we would certainly expand our investigation into this dimension.

4 Part 3: Let Nature Take Its Course?

4.1 Assumptions and Justifications

- **Assumption:** An increase in natural disasters will deter visitors from attending a national park.

  Justification: Visitors are naturally concerned about their safety and will not attend a national park if it is unsafe.

- **Assumption:** There is a correlation between vulnerability and monetary expense

  Justification: A higher vulnerability means that there is a higher risk of natural disasters. This means that the park must pay more to pay for those natural disasters, affecting the costs.

- **Assumption:** Monetary Expense can be justified by high visitor counts.

  Justification: Each visitor pays money when attending a national park, contributing to its revenue.

- **Assumption:** We should allocate funds to parks that have a combination of the most visitors and the least vulnerability.

  Justification: This combination is further highlighted in the model, but we want to ensure that if a park has most visitors and is least vulnerable, it gets the most funds.

4.2 Model

Before we begin, let us consider what draws us to the national parks. Every park has a unique characteristic that entices and attracts visitors, whether it be its geography, its wildlife, or its vistas. At the same time, as we have seen above, national parks present a venue for a wide range of dangers to the unfortunate traveller, from hurricanes to deadly temperatures. Yet, something about these natural spaces keep die-hard fans coming back for more.

While these sentiments are vague and anecdotal, could they inspire some way to objectively quantify the "allure" of a national park? Specifically, to quantify the value of a national park in terms of its patronage in visitor and overall worthiness of preservation? Computing such a property would allow us to compare the relative cost/benefit of maintaining each park and select the most important parks to fund in the future.

Word2Vec [6] is a method to represent words as high-dimensional vectors. Through machine learning, Word2Vec "trains" vectors to capture all the nuance of a word's connotations and relationships in a mathematical quantity. This ingenious advancement has a number of fascinating properties. For one, words that are related to each other, such as the set of numbers and the set of colors, are grouped together closely in the vector space. Furthermore, the vector difference between word pairs with parallel relationships, such as Man $\rightarrow$ Woman and King $\rightarrow$ Queen are themselves vectors with similar magnitude and parallel orientation.

For our final model, we present Park2Vec, a similar method that leverages the vector representation of our vulnerability scores to map scores describing similar locations closer to one another. By then visualizing these placements using a special algorithm designed to project entities with high-dimensionality on the two-dimension of a monitor, we could see and determine the groupings of locations with higher financial value as compared to those with less.

We define a vector $\vec{a_p}$ to be the Park2Vec representation of a particular national park p. Let us also name $\vec{v_p}$ to be the vector respresentation the park's vulnerabilities, as defined in section 4.2. We give $\vec{a_p}$ meaning in being the relationship between vulnerabilities of the park and its popularity P_p, a scalar measruement of annual visitor count. This is a very meaningful quantity: a park with few vulnerabilities but high popularity is much different that a park with many vulerabilities and low popularity. Therefore, we define $\vec{a_p}$ to be

$$\vec{v_p} \cdot \vec{a_p} = P_p$$

Essentially, $\vec{a_p}$ represents a vector to scalar function that takes the vulnerabilities (a vector) at a certain site and converts it to popularity (a scalar) in terms of visitors giving a comprehensive description of the site.

Using the data from the NPS Visitor Stats resource, we substitute annual visitor counts for each particular park into P_p in order to find a "best fit" value for $\vec{a_p}$. We accomplish this by thinking of these as a large system equations and using a least-squares optimization algorithm to fit $\vec{a_p}$. Note that since this is a dot product, our $\vec{a_p}$ in this problem is a vector in dimension R^5, the same as $\vec{v_p}$.

With this method, we computed Park2Vec vectors $\vec{a_p}$ for each of our five parks.

4.3 Results

Below is the graphical representation of our vulnerability vectors augmented with popularity and sea-level rise considerations. Entities in the green space are the best and should receive the most funding, followed by ones in the yellow. Ones in the white are least financially worthwhile.

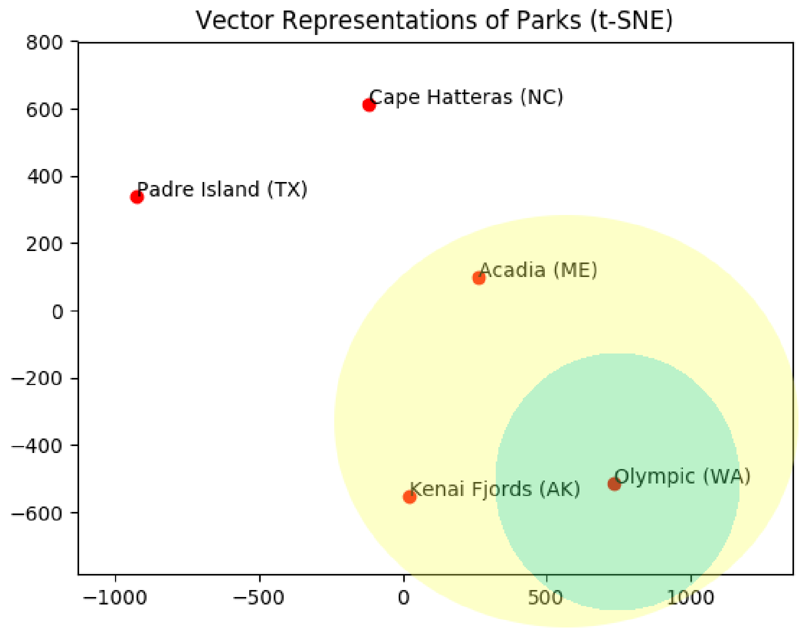


Figure 7: A t-SNE visualization of our Park2Vec results.

We used t-SNE [12] to create the 2-dimensional representation of our high-dimensional vector Park2Vec vectors. Roughly speaking, t-SNE reduces the dimensionality of a vector space by flattening it, revealing the interesting relationships between vectors in the space. Note that the axes of this graph are abstract in nature. Most notably, vectors that are nearby in the full vector space are clustered together similarly in the 2D representation.

4.4 Analysis

The placement and assosciation of the vectors makes assuring, logical sense. For example, with a high popularity and relatively low risk from natural disasters and sea level rise, the Olympic National Park would clearly be the most favorable location to direct funding. With its high occurence of forest fires and likelihood of being flooded, Padre Island is fairly far from the epicenter of allure.

Such a representation expands even beyond these five parks. Any location can be given a vector representation as described in the previous parts and plotted on this figure. Parks in the green zone are recommended to be funded, yellow are areas for further consideration, and whites are recommended to be let go in the event the NPS finds itself short on funding.

4.4.1 Strengths

One of the strengths of this algorithm is that it utilizes a prize winning machine learning algorithm known as t-SNE. This algorithm, presented in this paper [12] is one that takes a vector in multi-dimensional space, and reduces it to two dimensional space for visualization and simplification purposes. Another strength of this algorithm is that it is relatively simple in that it only takes into account our previous vulnerability scores and the visitor statistics data.

4.4.2 Weaknesses

Regardless of the simplicity of the algorithm, since the t-SNE algorithm simply projects five dimensional vectors into two dimensional space, it has the potential to greatly oversimplify the problem. In the future, we wish to discover more connections between the data and the visitor statistics and use that to avoid oversimplifying the problem. Perhaps if given more time, we would have looked at correlations between previous natural disasters and visitor statistics.

Another weakness of our model is that it does not talk specifically about cost, rather it talks about overall utility. The $\vec{n}$ that we use connects the vulnerability to the people that come back. In doing so, this vector consists of all possible factors lumped into one, which does not specify cost very well. Regardless, since cost is generally affected by any factor that would affect visitation rates, such as natural disaster frequency, we can model cost as an approximation of this vector $\vec{n}$.

5 Final Thoughts

Overall, we have presented models capable of determining the risk level of various coastal locations from sea level-rise, as well as provided a vector-like representation of vulnerability scores along with a grouping methodology that leverages such a representation. It is our hope the National Park Service will find the results of this analysis useful in planning their future approaches in preserving the nation's immeasurably priceless flora, fauna, and scenery.

Expanding beyond the NPS, it is undeniable the impact global climate change and sea level rise will have not only on the nation's ecologies, but the ecologies of the world. Looming throughout the analysis has been the shadow of climate-change driven sea-levels and the potentially catastrophic effects they will have on many coastal parks. Such effects transcend the ability of even the NPS to handle, and call on all of us, rangers, modellers, and humans alike, to take care of our planet's natural treasures and together, be the stewards of the world.

References

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