Optimizing Surfing with Mathematical Programming

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ABSTRACT

The goal of our project is to determine the best time and location to go surfing on a given day using binary integer programming techniques. Our model utilizes offshore ocean buoy data and local traffic data to make decisions about the optimal ocean and traffic conditions of the beaches and times our model considers. We test four instances of our model with varying levels of restrictiveness on data corresponding to three different days, and find that our model generally tends to favor sessions at Huntington Beach at early times. However, analysis of the data indicates that certain choices made by the model are nonsensical, and additional modifications ought to be implemented. Upon the completion of such modifications, we believe our work can find useful applications as a pseudo-recommendation tool to surfers, allowing them to pare down a list of potential beaches and times to a list of top contenders which they can then choose from according to personal preferences.

EXECUTIVE SUMMARY

The goal of this project was to propose, formulate, and test a binary integer program which selects an optimal time and location to go surfing on a given day. At a high level, our model attempted to balance two main considerations that we believe are most important in determining the quality of a surf session: wave quality and commute time. In particular, we sought to select the beach and time with the best quality waves and the lowest commute time. The goal is to help surfers make better informed, data-driven decisions regarding when and where to surf. Such a tool has significant relevance and demand within the surf community—nobody wants to sit in traffic only to arrive at a surf spot with sub-par conditions.

We gathered relevant traffic and wave data for three days: Friday 12/9/22, Saturday 12/10/22, and Tuesday 12/13/22. We then tested four different instances of the model with varying levels of restrictiveness on each of three days. While different optimal selections were made depending on the day and instance of the model, we found in the aggregate that Huntington Beach is favored by the model, and importantly that the model never selects surf times after noon (i.e. in the second half of the set of time periods considered by the model). This is aligned with decisions we believe experienced surfers would make, as morning waves are usually of better quality and commute time is usually lower. Additionally, Huntington beach is a close beach that has consistently good waves.

While our model showed it was capable of making logical decisions, it did not on two of the three datasets we provided. We found it struggled when conditions such as storms occurred, and was unable to capture how small scale condition changes impacted the quality. For instance, the model selection from Saturday's data shows that our model struggles when ocean conditions fluctuate throughout the entire day, and do not follow a general pattern. Ultimately the model requires more work and testing before it could be functionally used to predict which beach and time are optimal. We also believe that since it struggles to determine the effects of minute condition changes, its best use would be for narrowing down a large selection of beaches and times to a few preferable options. Then, surfers can then select the ideal beach and time from this subset based upon personal preference.

By providing a predictive service based upon an improved version of our model, surf companies can increase the ease with which surfers can choose a beach. Additionally, it would make surfing accessible to surfers who may not be as confident in their ability to determine surf quality from raw data.

TECHNICAL REPORT

I. Introduction

The primary stakeholder in this project is the average surfer, who in deciding where to surf is looking for a beach with waves that will generate the most exciting and satisfying experience. Should such a surfer choose a beach and time to surf without considering the relevant factors that shape the experience, they risk potentially spending the better part of a day on a surf session consisting of mostly waiting around for a wave in the water and in traffic. To our knowledge, a tool such as ours which uses data to optimize certain features of a surf session does not yet exist, and hence the average surfer stands to benefit from the development of our model.

Our model considers the quality of the waves at a given beach and the commute time to and from that beach, and seeks to select a beach and time for the surfer which balances these two categories of consideration. We develop a binary integer program, the outputs of which specify the beach and time the user will surf during as well as a score which reflects the overall quality of that selection.

The model is restricted to considering times throughout a single given day that the surfer hopes to surf during. In this report, we run the model on three different days, all with varying wave and traffic conditions. We find that the model tends to select sessions at nearby beaches during early times, which likely reflects the importance our model places on commute times. However, we find that on certain days, variation of important parameters can force the model to alter its choice.

We proceed by discussing data collection as well as a detailed description of our model. Then, we present the results the model generated and their interpretation, followed by an analysis of the model, including its limitations. We conclude by discussing potential applications of our work.

II. Model Formulation

The necessary data for this project falls into the categories of beach condition data and traffic data. Beach condition data consists of swell period, swell height, wind direction, and wind speed for each beach on a given day. Traffic data consists of the estimated commute times to and from each beach during the given window of time the surfer chooses to surf. Beach condition data was sourced from Surfline, a website that provides detailed conditions for many locations. Surfline acquires their data from a network of offshore buoys. This comprises thousands of buoys placed at varying depths to provide a robust estimate of ocean conditions at each beach. While our model runs based upon the day in which someone chooses to surf, sample data for a chosen day (Friday 12/9/22) is provided in the appendix. Commute time ranges were sourced from Google Maps, which provides a commute time estimate based upon day and arrival/departure time. Each hourly commute time was calculated by averaging the time range given by Google Maps at each hour of the day. For instance, if a 6am arrival time had an estimated drive time of 55 minutes to 75 minutes, we used 65 as the commute time for 6am.

Our model first assumes that the surfer resides in Claremont, California, and will therefore surf only at beaches within driving distance from Claremont. Hence, the model considers only a subset of common surfing beaches in Southern California. We also assume that the surfer is willing and able to surf anytime throughout the day from 6am to 8pm, and will only surf for two hours. Additionally, the surfer will arrive at the beach on the hour, and leave two hours later on the hour to return to Claremont. While there are many environmental factors that affect the quality of waves at a beach and their amenability to surfing, we restrict our considerations to only wave height, wave period, wind direction, and wind speed to make the modeling process tractable. Moreover, we assume that wave conditions remain the same over the course of a two-hour period. We further assume that the surfer is experienced and likes to surf in more extreme conditions. This assumption allows us to build our model with a preference for higher wind speeds and larger wave heights. We also assume that there is an upper bound to the amount of time the surfer is willing to drive in the given day.

Our model works by first computing a collective wave score based on the wave height, wave period, wind direction, and wind speed at a given beach and time, as well as a collective commute score based on the driving time to and from a given beach. Each beach and time is then assigned a combined score reflecting the overall wave and traffic conditions, and the beach and time with the highest score, subject to certain constraints, is then selected. In particular, our model is a binary integer program with decision variables indicating the optimal selection of beach and time for our surfer.

We now lay out the sets, parameters, and decision variables of our model.

Sets

Beaches (B): Contains the five beaches our model will consider. They are Huntington, Upper Trestles, El Porto, Trails, and River Jetties.

Times (T): Contains the set of times throughout the day, discretized as one-hour periods, that the model considers.

Parameters

$h_{i,j}$ measures the wave height for beach i during time j

$p_{i,j}$ measures the wave period for beach i during time j

$d_{i,j}$ measures the direction of the wind at beach i during time j

$s_{i,j}$ measures the wind speed at beach i during time j

$t_{i,j}$ measures the drive time to beach i arriving at time j

$f_{i,j}$ measures the drive time from beach i leaving at time j

$W_{i,j}$ is an aggregate wave score for beach i at time j as a value between 0 and 1

$C_{i,j}$ is an aggregate commute score for beach i at time j as a value between 0 and 1

B_1 denotes the maximum permissible difference between the commute and wave score at the beach and time the model will select

B_2 denotes the maximum permissible drive time for the beach and time the model will select

Decision variables

$x_{i,j}$ is a binary variable which equals 1 if the surfer will surf at beach i beginning at time j and 0 otherwise

Our model follows the following basic structure: for all i and j, the parameters $h_{i,j}, p_{i,j}, d_{i,j}, s_{i,j}$ are used to determine a wave score, $W_{i,j}$, for beach i at time j, and the parameters $t_{i,j}, f_{i,j}$ are used to determine a commute score, $C_{i,j}$, for beach i at time j. The beach with the largest combined score $W_{i,j} + C_{i,j}$, is then chosen. Hence, the objective function is

$$\text{maximize} \sum_{i,j} (W_{i,j} + C_{i,j}) x_{i,j}$$

and since we want the model to select only a single beach and time we impose the constraint that

$$\sum_{i,j} x_{i,j} = 1.$$

Because we determine that the surf session will last only two hours, the last two elements of the Times set exist only to correctly assign a proper commute score to the times before them, and they cannot themselves be selected by the model. Hence we mandate that for all i in Beaches,

$$x_{i,|T|-1}, x_{i,|T|} = 0.$$

Moreover, we want to avoid selecting a beach whose commute score is very good but whose wave score is very bad and vice versa. Hence, we impose the constraint that, for all i in Beaches and j in Times,

$$|W_{i,j} - C_{i,j}|x_{i,j} \leq B_1.$$

To determine the commute score for beach i at time j, we simply normalize the drive time to and from the beach to a value between 0 and 1, and then take a convex combination of these normalized values to receive a combined commute score between 0 and 1. To capture the fact that we want a longer commute time to generate a lower commute score, we add one to the negative of the convex combination. Specifically, for all i in Beaches and j in Times, j≠|T|-1,|T|

$$C_{i,j} = 1 - \left(\frac{1}{2}\frac{t_{i,j}}{max_j(t_{i,j})} + \frac{1}{2}\frac{f_{i,j+2}}{max_j(t_{i,j+2})}\right).$$

We also assume that our surfer does not want to spend more than a certain maximum number of hours driving in total, and so for all i and j we enforce that

$$(t_{i,j} + f_{i,j+2})x_{i,j} \leq B_2$$

We employ a similar method to compute a combined wave score between 0 and 1. The wave score is a convex combination of the wave height, wave period, and wind speed. Each of these values itself gets normalized using a similar technique to the commute score. The wave height term is weighted to reflect the fact that as the wave period increases, the height of the wave becomes less important to the quality of the surf experience, and likewise when period decreases, it is more important that the wave height is large. Also, the wind speed term is weighted by the term $g(d_{i,j})$, where g is a function defined in the following manner:

$g(d_{i,j}) = .2$ if $45 \leq d_{i,j} \leq 135$

$g(d_{i,j}) = .1$ if $135 \leq d_{i,j} \leq 225$

$g(d_{i,j}) = .2$ if $225 \leq d_{i,j} \leq 315$

$g(d_{i,j}) = .3$ if $315 \leq d_{i,j} \leq 360$ or $0 \leq d_{i,j} \leq 45$

Thus, the weighting of the speed term reflects the fact that when the wind is directed east, it is more important to have high wind speeds, while when the wind is facing west a surfer will care less if the wind speed is not as high. Note that computation of the value $g(d_{i,j})$ will occur during collection of the data before it enters the model.

All together, the wave score for a given i and j is then

$$W_{i,j} = (1 - \frac{p_{i,j}}{max_l(p_{i,j})})\frac{h_{i,j}}{max_j(h_{i,j})} + b_{i,j}\frac{p_{i,j}}{max_l(p_{i,j})} + g(d_{i,j})(1 - \frac{s_{i,j}}{max_l(s_{i,j})}),$$

where

$$b_{i,j} = 1 - (1 - \frac{p_{i,j}}{max_l(p_{i,j})}) - g(d_{i,j}).$$

III. Results

Table I: Optimal beach, time, and combined score for three days with varying parameters

	$(B_1, B_2) = (2, 180)$	$(B_1, B_2) = (.2, 180)$	$(B_1, B_2) = (2, 120)$	$(B_1, B_2) = (.2, 120)$
Friday 12/9/22	River Jetties 11am 1.767	El Porto 12pm 1.733	River Jetties 6am 1.557	River Jetties 6am 1.557
Saturday 12/10/22	Huntington 9am 1.711	Huntington 9am 1.711	Huntington 9am 1.711	Huntington 9am 1.711
Tuesday 12/13/22	Huntington 6am 1.797	Huntington 6am 1.797	Huntington 6am 1.797	Huntington 6am 1.797

The above table displays the beach and time suggested by the model on each of the three days considered for the given parameter pair (B_1, B_2). Notice that since the wave score and commute both never exceed 1, their absolute difference will never exceed 2, and so a value of $B_1 = 2$ imposes no real constraint on the variation between the wave and traffic qualities of the chosen beach. Likewise, a value of $B_2 = 180$ represents a maximum allowable driving time of 180 minutes, or 3 hours, for a session at a given beach and time. Hence the pair $(B_1, B_2) = (2, 180)$ represents the most permissible instance of the model, where effectively no constraints are imposed on the selection of beach and time, while the pair $(B_1, B_2) = (.2, 120)$ represents a more constrained version of the model. The combined score, i.e. the sum of the wave and commute score, is also shown for each of the model's selections.

Across the four possible pairs of parameters, the model makes three different selections of beaches and times for a session on Friday 12/9. In particular, the optimal score for this day drops significantly once the total driving time is constrained to be under two hours, which suggests that the best wave conditions on this day were accessible only via unusually long drive times. On the other hand, the optimal beach and time on Saturday 12/10 and Tuesday 12/13 remain unchanged across all four parameter pairs. Intuitively, this fact suggests that the wave and traffic conditions at the optimal beach and time for these days met the constraints attained by the strictest pair of parameters, specifically $(B_1, B_2) = (.2, 120)$, and that the imposition of stricter constraints only eliminated the feasibility of beaches and times with lower scores.

IV. Conclusions and Analysis

Overview

As evident in Table I, our model strongly favors Huntington–out of the 12 instances of the model evaluated, 8 of them selected Huntington as the optimal beach. As mentioned above, on Saturday and Tuesday, the model chose Huntington in all four instances of varying levels of restrictiveness. Hence, Huntington appears to be the most reliable place to surf given varying wave and traffic conditions. It is also important to note that our model never makes a selection past 12pm. Morning surf sessions are overwhelmingly favored in all cases. Keeping this in mind, our Friday data seems like an outlier compared to Saturday and Tuesday. Relative to the other days, our model makes three different selections on Friday. This seems to indicate that something out of the ordinary is happening with respect to the wave or traffic data. We will explore this more in the coming discussion.

Analysis

In order to determine if the selections made by our model are logical, we will go day by day and compare the model results to the raw wave and traffic data. This analysis stems from past surfing experience and knowledge of how ocean conditions impact the quality of waves at any given location. Note that Surfline does not provide the ability to access past surf forecasts, so comparing our model results to the predictions given by Surfline is not feasible.

The model selections on Friday vary the most when compared to Saturday and Tuesday. The selection for the most flexible case is River Jetties at 11am. The wave height at this time is ~1ft, and the wave period is 5 seconds. Off the bat, this is a concerning selection. At any surf spot, a swell of 1ft @ 5sec will almost certainly result in no waves–there is just not enough energy to create significant waves. This fact is especially true at a beach like River Jetties, which generally requires slightly more swell to provide significant waves. The other selection of El Porto at 12pm is similarly concerning—the swell is approximately 1.3 ft @ 5sec, which is equally insignificant. The logical choice for Friday would probably be Trestles at 6 am, as the swell in this time period is approximately 1ft @ 12 sec, which will usually correspond to small, but fun, waves. The likely explanation for the extreme discrepancy in wave period between Trestles and River Jetties and El Porto is that the swell direction was approximately due South, which would favor Trestles and Trails more than the other locations. While swell direction is not a parameter used by our model, it can provide helpful insight into why our model made an objectively bad decision on Friday.

On Saturday, our model chose Huntington at 9am for all cases. Looking at the wave data, the swell at this time was approximately 0.6ft @ 10 sec. While a swell of this size could result in some extremely small waves, choosing this above other spots is a gamble that most reasonable surfers would probably not take. At best, the conditions would be sub-par. In this case, looking at the wind speed gives us a pretty certain reasoning for why our model made this decision. Throughout the entire day the wind speed at all locations ranged between 10 and 20 knots, with most times having winds in the upper end of this range. Additionally, the wind direction was onshore for the entire day (West winds, 0.1 and 0.2 in our wind direction parameter). The combination of powerful, onshore winds at all locations tells us there was storm activity on Saturday. The effect of this storm, besides the winds, was variable surf conditions that resulted in fluctuating buoy data for wind speed and direction. The bottom line is that our model was given a highly variable dataset here—values for wave height and wave period continually changed across all locations, all day long. Given this fact, our model actually made a pretty good choice by selecting a time in which the wave period was larger, the wave height was smaller, and the wind was 'relatively' light. Overall though, Saturday would not be a good day to surf, and our model did not identify that. While the limitations of our model will be further discussed below, we may note now that the formulation presented in this report does not account for variable conditions due to storm activity.

On Tuesday, our model chose Huntington at 6am for all cases. In contrast to the other selections made by our model, this choice is completely logical, and the one most surfers would likely make when presented with the Tuesday data. The swell is approximately 1ft @ 13 sec, which will usually result in small, fun waves. The winds are light and favorable, as well. Traffic to and from Huntington is also light.

To summarize, our model made the logical decision on when and where to surf on one out of the three days. The selection on Friday was completely illogical, and objectively the wrong choice. Most likely, this is due to the fact that swell direction is not a parameter considered by our model; the swell direction on Friday was extremely South, which favored some spots more than others. On Saturday, the model was presented with a difficult choice due to the storm (a relatively unusual occurrence in Southern California). While our model chose a time and place to surf that did not have favorable conditions, given the nature of the data we believe the selection was on par with the way in which our model was formulated. On Tuesday, our model made the correct selection on when and where to surf.

Limitations

While our model has shown that it is in certain cases capable of making reasonable decisions on when and where to surf, it is also clear that some issues are present which frequently causes our model to make illogical decisions. These flaws present significant limitations with respect to the practical use of our model. Overall, the limitations of our model can be separated into two main categories: things our model struggles with and things our model does not consider.

In order to provide context for why parameters not considered by our model could be helpful, we first start by describing the cases in which our model has trouble making logical decisions. First, with respect to the wave score, our model does not do a good job of considering the relationships between different parameters. The best example of this is when our model chose to surf at River Jetties at 11am when the swell was 1ft @ 5sec. If the swell period was greater than ~13 seconds, a 1ft swell would result in waves. This relationship between swell height and period is only one example of how parameters in our model are all interconnected, and have direct effects on each other. As it stands, however, the model formulation does not reflect this. Our model also tends to make poor decisions when overall conditions are bad everywhere. More specifically, when there is little swell in the water, our model fails to make distinctions between different surf spots—the differences in wave quality are pretty negligible, so small changes in conditions at certain times cause the model to make illogical decisions.

Next, we address aspects of wave or traffic data that our model does not consider. First, our model has one set of rules for determining the wave score. Realistically, there are many different frameworks that could be used, each placing varying weights on different components of the waves. Our model would be more accurate if it made multiple selections based on the different approaches, and then made a final decision based on those selections. Additionally, our model does not factor in the uncertainty inherent to our parameters. The best way to address this would be using robust optimization techniques in which our parameters are not given fixed values but a set of values that reflect the uncertainty in their measurements. Future iterations of this project would benefit from such an approach.

It is important to mention that our model does not consider how different waves prefer different ocean conditions. Further, our model evaluates wind direction in four ways: N, S, E, W. Really, it would be more accurate to consider this as a range—a wind direction directly in between N and S should be considered independently of N or S in order to make an accurate prediction. Our model also does not consider secondary swells in the wave quality score. Taking secondary swells into consideration is important when making decisions on where to surf. For example, a primary swell of 4 feet @ 15 seconds with a secondary swell of 1.5 feet @ 22 seconds with a slightly different direction means that the primary swell is most likely a longer period swell than the model thinks. Additionally, our model does not consider the tide in the wave quality score. Overall, these parameters are all important factors that influence wave quality, and our model would benefit from the addition of these metrics.

Applications

Our initial stakeholders for this project were individual surfers, who we believed would be able to use our model to determine a singular best location to surf. However upon analysis of the results it is clear that the model, while able to make logical decisions, frequently struggles to do so. We have also seen that it struggles to properly weigh and analyze smaller scale changes in conditions and abnormal weather such as storms. For this reason we believe that an improved version of our model best serves those surfers who would like to refine an extensive set of possible surf locations down to a smaller subset of options. This alternative would help surfers save time and energy, as the model would weed out obviously poor options allowing the surfer to then analyze the ones it deems most fit. In this way, a less precise model would still produce helpful results. By including a version of our model in their service, companies such as Surfline would make choosing a beach more time efficient and would make surfing more accessible to surfers who are not as adept at reading beach conditions.

Conclusion

Overall, we see that our model finds Huntington to be the most reliable location given the consistently favorable wave and traffic conditions. Given interpretation of the raw data, we believe this selection to be valid. Based on our sample data, our model made illogical selections most of the time. While this was partly due to the variable conditions of Saturday's wave data, our model's inability to adapt to unusual conditions highlights the limitations of our model in being a tool that can be utilized by surfers to determine the best time and place to go surf on a given day. We believe our model could be improved by adding conceptual complexity and incorporating robust optimization techniques. Additionally, we believe that such an improved model would benefit from the addition of more parameters for the wave data. Lastly, given our analysis of our results, we believe that our stakeholders should shift from being individual surfers to a surf forecasting company that would benefit from having a feature that helps users with little ocean experience narrow down the best options on where to surf on a given day.

APPENDIX

Friday 12/9/22 Data

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	53	65	73	78	75	65	68	68	68	73	78	78	78	73	63
El Porto	65	80	88	90	78	73	73	73	73	80	93	93	100	98	83
Trestles	65	75	78	83	80	73	75	75	78	83	88	90	90	83	73
Trails	70	75	85	85	90	83	83	83	85	85	90	90	98	90	85
River Jetties	50	63	73	83	68	65	65	65	65	68	70	70	75	68	58

Table 2: Friday Drive Time To (minutes)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	53	55	60	65	63	65	73	78	88	105	113	115	115	98	83
El Porto	58	60	68	78	70	70	80	83	100	113	135	145	140	128	128
Trestles	70	65	70	73	73	73	83	90	93	100	113	123	123	103	83
Trails	70	70	75	78	78	78	125	90	95	108	120	125	123	110	85
River Jetties	48	50	55	58	58	60	65	78	85	100	108	118	118	103	78

Table 3: Friday Drive Time From (minutes)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	3	4	3	4	5	4	4	5	5	5	5	5	5	5	5
El Porto	4	4	4	5	5	5	5	5	5	5	5	5	5	5	5
Trestles	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Trails	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
River Jetties	4	4	4	4	4	5	5	5	5	5	5	5	5	5	5

Table 4: Friday Wave Period (seconds)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	0.7463	0.6527	0.5739	0.8952	0.8726	0.4979	0.4899	0.4847	0.4791	0.4789	0.4639	0.4584	0.4854	0.5031	0.505
El Porto	1.2341	1.2843	1.3103	1.3148	1.3102	1.3156	1.3192	1.3423	1.3733	1.4012	1.414	1.3967	1.3544	1.3125	1.3112
Trestles	0.8459	0.7832	0.7779	0.7741	0.7359	0.7353	0.7744	0.8124	0.8186	0.8403	0.8438	0.8459	0.8451	0.8469	0.8397
Trails	0.7604	0.7561	0.7652	0.7625	0.7241	0.7604	0.7743	0.8091	0.8255	0.8308	0.8361	0.8377	0.8357	0.8357	0.8266
River Jetties	0.9754	0.9643	0.9653	0.985	1.012	1.0404	1.0634	1.084	1.1019	1.122	1.1474	1.166	1.1984	1.2302	1.2412

Table 5: Friday Wave Height (ft)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.1
El Porto	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Trestles	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3
Trails	0.2	0.2	0.2	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.3
River Jetties	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2

Table 6: Friday Wind Direction

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	1.9596	2.3926	1.7277	3.0669	3.5493	3.2198	4.0237	3.5784	3.9038	5.3299	4.8514	3.9541	2.5685	1.2157	0.9584
El Porto	4.136	4.9362	5.219	5.4688	4.7157	2.9023	3.1343	4.9484	5.7468	5.1701	4.1522	3.9255	4.357	3.4927	4.2544
Trestles	5.654	5.0169	3.8279	0.8176	1.8997	4.5362	6.426	6.5139	6.4248	5.6495	4.8385	4.1459	2.8197	2.1474	2.7584
Trails	4.169	3.2863	2.0758	1.2745	1.8623	4.355	6.7007	6.7365	6.5853	5.9365	5.2399	4.4649	3.3594	3.094	3.816
River Jetties	2.3943	2.5074	1.7377	2.7573	3.7807	3.5843	4.2452	3.7771	3.9013	5.0168	4.7907	3.7236	3.3516	1.8033	0.7069

Table 7: Friday Wind Speed (knots)

Saturday 12/10/22 Data

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	53	53	55	55	58	63	65	68	68	68	65	65	68	65	58
El Porto	53	55	55	58	60	63	68	73	78	78	78	80	80	85	70
Trestles	65	65	63	65	68	68	70	73	73	75	75	73	73	73	70
Trails	70	70	70	70	73	73	73	78	83	83	83	78	78	78	75
River Jetties	48	50	50	55	55	58	65	65	65	65	63	63	65	63	55

Table 8: Saturday Drive To (minutes)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	53	53	50	50	58	58	65	70	78	78	80	85	85	78	65
El Porto	58	58	58	58	60	63	70	73	80	88	93	93	88	85	70
Trestles	65	65	63	65	68	70	78	85	90	85	85	85	85	85	75
Trails	68	70	68	70	70	75	85	90	98	93	93	93	93	93	78
River Jetties	48	50	53	55	55	58	58	68	70	83	83	80	80	78	75

Table 9: Saturday Drive From (minutes)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	4	4	5	10	10	10	10	10	10	10	10	10	10	10	10
El Porto	10	10	0	10	10	10	10	0	0	0	13	13	13	13	13
Trestles	10	10	4	5	5	5	6	8	8	5	12	5	5	6	6
Trails	10	10	4	5	5	5	5	5	5	5	5	6	6	6	6
River Jetties	16	16	16	10	10	10	10	10	10	10	10	10	10	10	10

Table 10: Saturday Wave Period (seconds)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	3.2931	3.7454	4.5017	0.6241	0.6192	0.4942	0.5333	0.5364	0.5266	0.5249	0.5245	0.5442	0.5414	0.55	0.5137
El Porto	0	0.3334	0	0.2985	0.2846	0.2843	0.2892	0	0	0	1.388	1.5238	1.6095	1.6212	1.8549
Trestles	0.6086	0.6027	3.379	4.1473	4.4878	4.4216	3.5139	3.588	3.8571	3.6489	0.4441	3.829	4.1415	3.7864	3.8086
Trails	0.6047	0.5996	3.2859	3.893	4.1724	4.7056	4.6534	4.6432	2.9021	2.6478	2.4937	2.3553	2.0465	1.9963	2.0116
River Jetties	0.2365	0.2536	0.2432	0.5948	0.5867	0.5834	0.4927	0.4894	0.4895	0.4889	0.4853	0.5092	0.5061	0.5014	0.4943

Table 11: Saturday Wave Height (ft)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
El Porto	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Trestles	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.2	0.2	0.2	0.3	0.2	0.2	0.2
Trails	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.2	0.2	0.3	0.3	0.2	0.2	0.2
River Jetties	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2

Table 12: Saturday Wind Direction

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	16.15694	18.74598	17.60104	12.23083	9.50346	11.39521	10.89628	10.81773	9.18039	6.43996	9.53473	9.27486	8.98321	8.77402	8.5759
El Porto	15.6965	17.68979	14.57405	16.37744	10.31471	11.93311	12.07867	14.44105	15.18619	15.99071	16.61762	16.81722	16.54796	16.18232	14.01749
Trestles	15.58061	17.27353	17.92761	20.97751	11.38798	13.02944	13.68482	12.4757	11.66499	11.01256	12.90398	4.53489	10.53171	9.31716	7.4632
Trails	15.00843	16.90229	17.1405	19.75548	12.35968	13.66765	13.66361	12.7298	13.50791	10.84217	13.65148	5.33106	9.06918	10.16369	8.06979
River Jetties	17.437	19.70067	19.72165	14.93758	8.86972	10.17646	11.29273	10.76321	10.24471	6.46975	8.55205	9.60946	8.64443	8.83587	9.4313

Table 13: Saturday Wind Speed (knots)

Tuesday 12/13/22 Data

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	53	70	93	95	88	68	95	95	95	95	98	108	85	68	58
El Port	68	90	113	128	108	83	70	70	68	70	80	85	93	85	63
Trestles	65	80	93	98	88	75	73	70	73	73	83	88	95	80	68
Trails	70	85	103	100	95	83	78	78	78	78	85	90	98	90	73
El Porto	53	70	93	103	83	65	60	60	60	60	65	73	78	63	53

Table 14: Tuesday Drive To (minutes)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	53	55	63	70	65	63	65	68	73	88	100	100	120	113	73
El Porto	58	63	80	85	78	70	70	70	80	98	118	130	145	145	95
Trestles	65	65	73	78	75	73	73	75	78	85	98	105	110	103	83
Trails	70	70	78	90	78	78	78	83	85	93	100	113	118	100	90
River Jetties	50	55	60	68	60	58	60	65	70	85	100	108	120	115	68

Table 15: Tuesday Drive From (minutes)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
El Porto	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
Trestles	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
Trails	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
River Jetties	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13

Table 16: Tuesday Wave Period (seconds)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	1.08337	1.29367	1.29409	1.2916	1.29219	1.29101	1.28789	1.28373	0.92277	0.93064	0.94757	0.73602	0.73022	0.83455	0.86667
El Porto	1.11893	1.12441	1.13054	1.12651	1.20666	1.15705	1.33776	1.34833	1.37169	1.37044	1.38845	1.35292	1.34984	1.37054	1.36893
Trestles	1.28415	1.28009	1.28061	1.32336	1.32933	1.33199	1.30709	1.21827	1.20978	0.84744	0.70358	0.69869	0.82713	0.81194	0.79423
Trails	1.27585	1.27428	1.27336	1.32231	1.31509	1.23688	1.2333	1.22283	0.85236	0.83596	0.6876	0.75919	0.75322	0.80013	0.78812
River Jetties	1.1294	1.04623	1.03278	1.23297	1.22936	1.22044	1.2144	1.20764	0.88002	0.8854	0.86998	0.91453	0.71355	0.76043	0.78766

Table 17: Tuesday Wave Height (ft)

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.2	0.2
El Porto	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.2
Trestles	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.2	0.2
Trails	0.2	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.2	0.2
River Jetties	0.3	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.2	0.2

Table 18: Tuesday Wind Direction

	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Huntington	2.6808	2.23055	1.24764	1.38626	1.16245	2.04094	4.41419	5.97754	5.48281	5.19831	4.94116	3.96585	2.12326	14.9086	15.9013
El Porto	3.46289	5.32632	5.5928	4.21169	0.67333	1.29058	5.12058	5.27809	5.11698	5.8397	6.04917	5.47757	3.46137	1.15496	2.34027
Trestles	4.8522	3.25493	0.7498	2.99494	4.16896	4.94186	6.82653	7.70436	6.85047	6.14302	5.36588	3.63087	2.51608	1.92243	8.1391
Trails	1.89381	1.58286	1.28616	2.75116	3.60661	4.23555	6.22836	7.37092	6.63213	6.10278	5.45084	3.55351	2.48676	2.53506	8.2858
River Jetties	2.6612	1.97354	1.15043	2.43532	1.76594	2.70185	4.76683	6.01656	5.31731	4.67446	4.03404	3.87235	7.51742	14.2555	13.7414

Table 19: Tuesday Wind Speed (knots)

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