Exploratory Cross-Scale Characterization of Oceanographic Data Surrounding Offshore Wind Areas

By:

Nusrat Noor

Dr. Patrick Halpin, Advisor

April 2025

NICHOLAS SCHOOL OF THE ENVIRONMENT

DUKE UNIVERSITY MARINE LAB

Masters project work plan submitted in partial fulfillment of the requirements for the Masters in Environmental Management degree in The Nicholas School of the Environment at Duke University

EXECUTIVE SUMMARY

The U.S. shift towards offshore wind and renewable energy is very encouraging, however, it is critical to ensure this is not done at the expense of marine wildlife and the marine ecosystem. We worked to support Project Wildlife and Offshore Wind (WOW), funded by the Department of Energy (DOE) and BOEM by conducting an exploratory cross-scale characterization of oceanographic data within offshore wind energy areas in the Northeastern U.S. Atlantic Coast. We focused on spatial and temporal coverage of Vineyard Wind 1, Empire Wind, Atlantic Shores South, and their surrounding regions. Our characterization focuses on spatial and temporal coverage that can potentially help downscale existing habitat-based density models by identifying when extrapolation is appropriate and guiding more targeted, efficient research and monitoring efforts.

In order to tackle this project, we acquired the following oceanographic data from multiple sources: sea surface temperature, chlorophyll A concentration, sea surface height anomalies, bottom temperature, wind speed, depth, sediment type, and seabed form. Glider path data was also acquired from the U.S. Integrated Ocean Observing System (IOOS) and overlaid on top of the study area. The wind lease energy sites were buffered by 10 kilometers prior to any calculations in order to remain consistent with other Project WOW analysis. The subregions were all cut off at the 500-meter isobath and the New York/New Jersey Bight area was split at the Hudson Canyon to subset out the Northern and Southern halves.

Zonal statistics was conducted to calculate averages or the relative percent coverage of all the variables for each study area. The resulting dataset was run through a Pairwise Euclidean Distance function in R, and a Multivariate Clustering analysis tool in ArcGIS Pro. The results were visualized as maps or heatmaps to provide insight into: 1) What kind of data is available within the study area and how is it distributed, 2) Is the available data able to be extrapolated from one site or region to another, and 3) Are the field study sites initially chosen by Project WOW (Vineyard Wind 1 and Empire Wind) representative of the areas they are in. For this third question, we added an additional 18 sites to our dataset and conducted another Multivariate Clustering analysis.

Key Findings:

1. Remotely sensed data is similarly available across the study sites, however, glider research activity is primarily concentrated in Atlantic Shores South wind farm site, and the Southern part of the New York/New Jersey Bight, south of the Hudson Canyon. Data collection is not evenly distributed and sites such as Vineyard Wind 1, had very minimal glider coverage. This is just for ocean glider data, and does not take into consideration other forms of data collection such as research ships or buoys.
2. Based on the variables we used, the larger regions north of the Hudson Canyon (NY/NJ Bight North and Southern New England) seem to be more similar to each other than to the region south of the canyon (NY/NJ Bight South). The wind farm sites themselves are clustering together, meaning they are more similar to each other than they may be to the regions they belong to. This is likely due to offshore wind farms being chosen specifically to fit certain criteria.
3. For the most part, the wind farm sites clustered together geographically. Vineyard Wind 1 and Empire Wind clustered not only within their regions but also clustered with each other. However, there were some discrepancies with a site near Massachusetts clustering differently. Additionally, the further south the sites were, the more different they became. While this means that for the initial field research, Vineyard Wind 1 and Empire Wind have similar environmental conditions, caution needs to be taken when extrapolating out to other sites, and especially further south. This analysis has some limitations as only oceanographic data was included, there was no ground-truthing of the remotely sensed data, and our analysis does not say anything about the magnitude of the clustering.

TABLE OF CONTENTS

INTRODUCTION

Offshore Wind Energy

The efforts to reduce CO_2 emissions while simultaneously meeting the population's growing energy demand, has led to nations setting goals such as reducing 40% of CO_2 emissions, a binding target of 27% for renewables, and a 27% increase in energy efficiency by 2030 (Díaz & Guedes Soares, 2020; European Commission, 2014). Offshore wind development has emerged as a key player in renewable energy, particularly due to current technological advances and industrial growth (Díaz & Guedes Soares, 2020).In addition to adding to the efforts to mitigate climate change, offshore wind energy is also critical to the growth of the blue economy. Historically, Europe and China have led the advancement of offshore wind development, however, in recent years, the U.S. has been shifting towards the offshore wind sector and playing a more prominent role on the global scale (Costoya et al., 2020).

The US is estimated to be able to reach up to 2000 GW of potential production through offshore wind (Costoya et al., 2020). Additionally, in certain highly populated states, it's estimated that offshore wind power has greater energy potential than their land-based counterparts (Mills et al., 2018). The US offshore wind energy pipeline has seen a 15% growth from 2022 to 2023, with goals to deploy 30 GW by 2030 and 110 GW by 2050 (U.S. Department of Energy, 2023). Much of the wind development has been along the Northeastern Atlantic coast, followed by the Western coast near Oregon and California, and the Gulf of Mexico with three wind energy areas (WEAs). States like Massachusetts, New York, New Jersey, and Virginia have emerged as frontrunners in offshore wind development (U.S. Department of Energy, 2023).

Through the Energy Policy Act of 2005, the Department of the Interior (DOI) gave the responsibility of offshore wind development in federal waters to the Bureau of Ocean Energy Management (BOEM). As such, BOEM has the authority to issue wind energy leases, easements, and right-of-way for activities on the Outer Continental Shelf (OCS) (BOEM, 2024). This is in conjunction with various state and federal agencies that have their own permitting authorities responsible for different parts of the permitting and impact assessment process (Methratta et al., 2020). Many of the decisions involving where to develop offshore wind farms take into consideration factors to reduce competition, mitigate viewshed impacts, availability of wind resources, and avoidance of military operation areas (Methratta et al., 2020). This requires a significant amount of collaboration between various departments and entities, and creating many partnerships such as that between BOEM and the National Oceanic and Atmospheric Administration (NOAA). The National Centers for Coastal Ocean Science (NCCOS), plays a critical role in providing BOEM with the scientific ocean knowledge and technical marine spatial planning tools to choose the "optimal locations for offshore wind development while minimizing conflicts to the environment and other ocean industries" (National Centers for Coastal Ocean Science (NCCOS), n.d.).

While the prospects of offshore wind development can be very encouraging, it is important to note that it is still very much a new frontier, especially within U.S. waters. Information on the ecological impacts of this shift towards more offshore wind development is still very scarce. A recent study evaluating the global impact of offshore wind development found that more than 86% of possible offshore wind farm impacts on ecological services are unknown (Watson et al., 2024). The impacts from construction were largely negative across ecological subject groups. The impacts of the operational phase were found to be more dependent on the specific location on whether they were mostly positive or negative (Watson et al., 2024). Significant portions of the research looking into the ecological effects of offshore wind development are focused on wind energy in Europe and do not often include migratory whales that are more of a consideration around US waters (Watson et al., 2024).

The rate of offshore wind development has sped up significantly, and as such, it is of utmost importance that impact analyses keep up with this pace. However, a challenge for the scientific community is being able to conduct these vital studies within the timelines for wind projects (Methratta et al., 2020). The Department of Energy (DOE) and BOEM funded Project WOW (Wildlife and Offshore Wind) to address gaps in understanding the environmental impacts from offshore wind energy development. Project WOW is led by Duke University and is a "trans-disciplinary highly integrated collaboration of diverse experts for the comprehensive evaluation of the potential effects of offshore energy development on marine wildlife" (Duke University, n.d.). Their goal is to develop a risk assessment framework for offshore wind development in the Atlantic region, focusing on marine wildlife such as marine mammals, sea turtles, sea birds, and bats. The research is predominantly focused on two study sites: Vineyard Wind 1 off the coast of Massachusetts and Rhode Island, and Empire Offshore Wind off the coast of New York and New Jersey **(Figure 1)**. This research will be integral to BOEM as they manage offshore wind development in the Atlantic, and potentially other regions as well (Bureau of Ocean Energy Management (BOEM) et al., 2023).

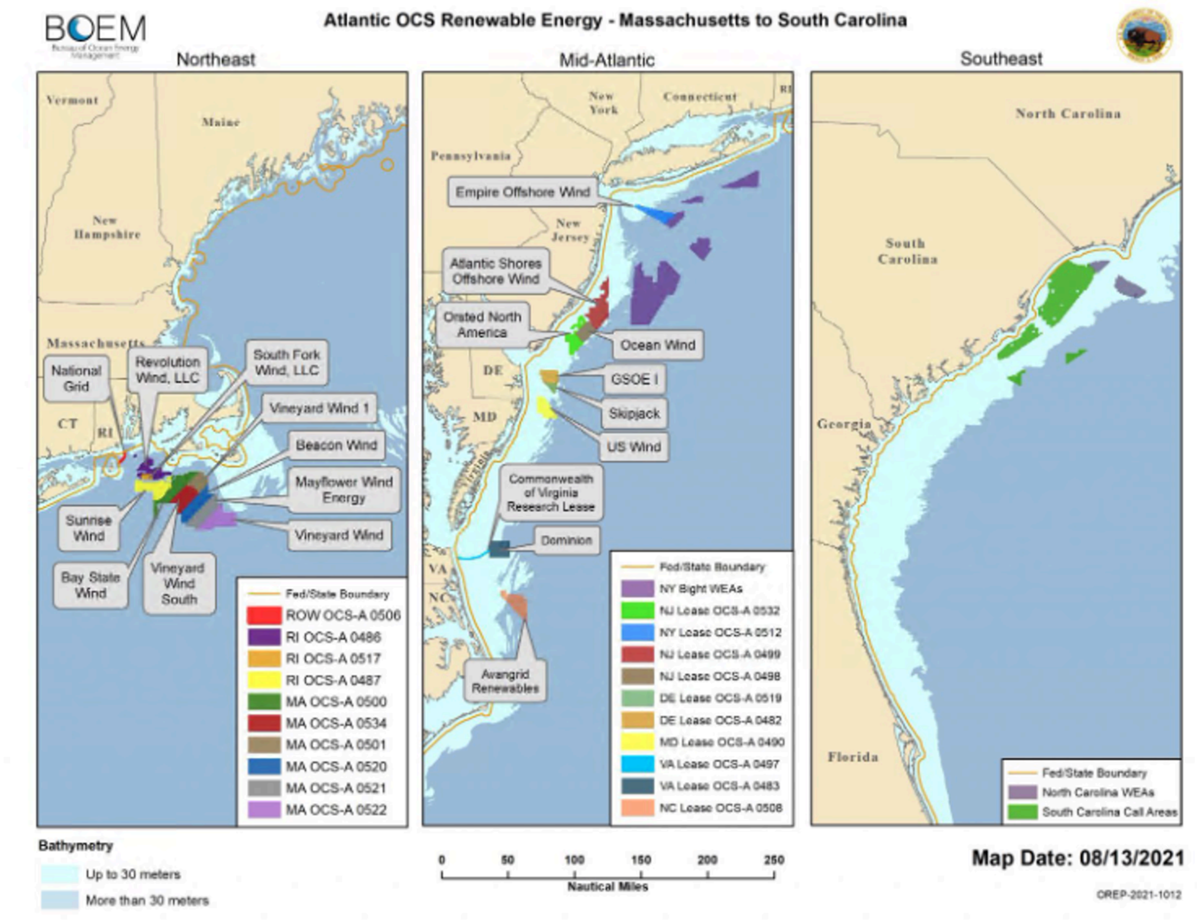


Figure 1: Atlantic Outer Continental Shelf (OCS) renewable energy areas (BOEM, 2024).

Statement of Objectives

We will be working on an initial cross-scale characterization of the data coverage within and between the Vineyard Wind 1 lease area, Empire Wind lease area, Atlantic Shores South lease area, and their surrounding subregions. The characterization would focus on spatial and temporal coverage that potentially can help downscale existing habitat-based density models. The project will include inventorying select oceanographic data to answer the following questions:

1. What kind of data do we have to characterize the regions as well as the immediate area surrounding the wind lease areas?
2. Are there differences/similarities in available data between sites and regions, i.e., can we extrapolate data from one wind lease area to another?
3. Are the offshore wind farm sites chosen for Project WOW representative of the wind farms in each subregion?

METHODS

1. Acquiring and Processing BOEM Offshore Wind Farm Site Data

The shapefiles used to define the study sites for this project were acquired from Deborah Brill, an associate in research in the Marine Geospatial Ecology Lab. There are six zones, three of which are the wind farm sites with a 10-kilometer buffer, and three of which are the larger subregions they fall into. The wind farm sites, and their respective subregions as depicted in **Figure 2**, are: 1) Empire Wind (EW) and the northern portion of the New York/New Jersey Bight subregion (NYNJB North); 2) Vineyard Wind (VW) and southern portion of the New York/New Jersey Bight subregion (NYNJB South); and 3) Atlantic Shores South (ASH) and Southern New England (SNE). The subregions were cut off at the 500-meter isobath, and the New York/New Jersey Bight was additionally separated along the Hudson Canyon to subset out the northern and southern parts. The feature class with all six polygons was saved as a shapefile and named, "Covariates_tool_polygon_all.shp". While the buffered wind farms were treated as their own areas, they were not removed from the larger sub-region polygons despite the potential for "double-counting". Because part of our analysis focuses on whether or not the statistics of the smaller wind farm sites are significantly different from their regional counterparts, and the sections are not directly comparable, we deemed it still appropriate to keep the sites nested inside each other.

To answer the third research question, additional wind farm polygons came from a shapefile containing the BOEM Wind Lease Outlines. This dataset was downloaded from the Northeast Ocean Data Portal via Marine Cadastre (03/23/25) (BOEM/OREP, 2018). While this feature class included polygons for Vineyard Wind, Empire Wind, and Atlantic Shores South, to make sure the data processing was the same for our sites during the second round of data processing and site clustering, we deleted the corresponding polygons from the BOEM Wind Lease Outlines shapefile and replaced the polygons with copies of the polygons received from Deborah Brill. The lease outlines included sites outside of the overall study area, so we clipped the feature class to what was within the study area bounds. We also removed the three main sites (VW, EW, and ASH), any partial polygons that remained after clipping, and all easements. We buffered each site by 10 km, removed unnecessary fields, appended copies of the VW, EW, and ASH shapefiles, and named our file “All_Sites_Buffered.shp”. We included an additional 18 sites, making the total number of wind farm sites 21.

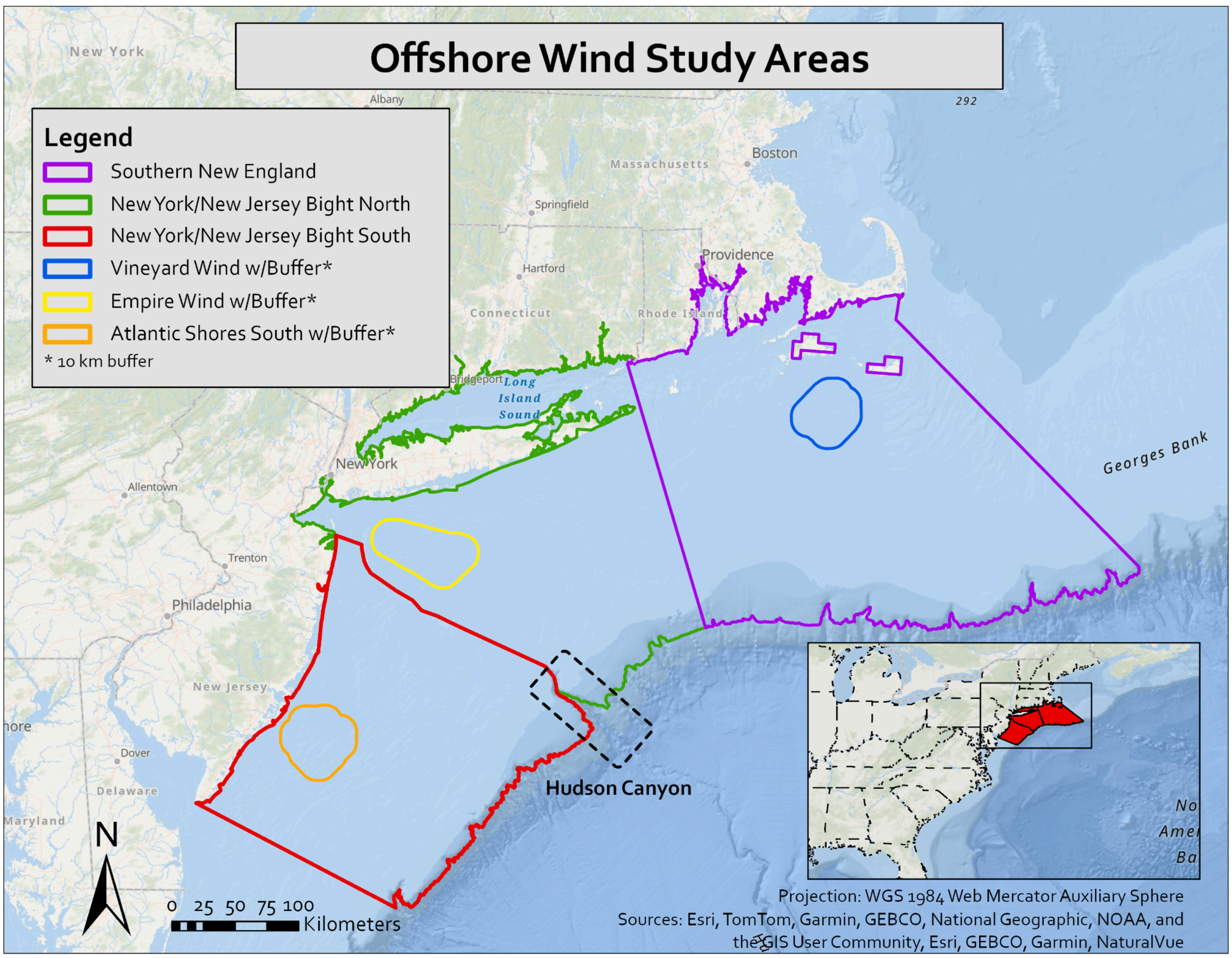


Figure 2: Map outlining the offshore wind study areas used for analysis. Vineyard Wind (VW), Empire Wind (EW), and Atlantic Shores South (ASH) each have a 10 km buffer.

2. Acquiring and Processing Oceanographic Data

We included eight variables for the Pairwise Euclidean Distance Analysis and the Multivariate Clustering Analysis **(Table 1)**. Sea surface temperature (SST), chlorophyll A concentrations, and sea surface height anomaly data (SLA) were retrieved from the ERDDAP at NOAA CoastWatch datasets through Jupyter Notebook using the xarray package (NOAA CoastWatch, n.d.; NOAA NESDIS CoastWatch, n.d.; Veronica Lance & NOAA/NESDIS/OSPO, n.d.). The data for each variable spanned the previous 5 years (2020 – 2024) and was separated by season. Each season is defined as follows: Winter – December to February, Spring – March to May, Summer – June to August, and Fall – September to November. Summary statistics, including the mean, minimum, maximum, median, range, sum, and standard deviation, were extracted for each study area/zone. Averages for each summary statistic were calculated and exported as a table. For example, the maximum Fall SST value for Empire Wind is actually the average maximum fall SST value for Empire Wind from 2020 to 2024.

VARIABLE	UNIT/COMPONENT
Sea Surface Temperature	℃
Bottom Temperature	℃
Chlorophyll A Concentration	mg/m^3
Sea Surface Height Anomalies	m
Wind Speeds	m/s
Depth	m
Sediment Type	Grain Size (mm)
Seabed Form	Slope & Relative Position

Table 1: Oceanographic variables used for analysis and their units and/or components.

Wind speed and 2021 bathymetry values were downloaded from the Mid-Atlantic Ocean Data Portal (NREL & BOEM, Office of Renewable Energy, 2015; NOAA/NCEI, The Nature Conservancy, 2020). Bottom temperature data, seabed forms, and sediment size data were taken from the Northeast Ocean Data Portal (Rachel Shmookler & RPS, 2019; The Nature Conservancy, 2016a, 2016b). If wind speed, bathymetry, and bottom temperature datasets were not provided in a rasterized format, they were converted to a raster, and the mean values for each zone were calculated using the 'Zonal Statistics as Table' tool. We exported the resulting tables to CSV files for further analysis in R.

The seabed forms and sediment size data needed to be reprojected to the GCS WGS 1984 coordinate system, after which the "Extract by Mask" tool was used to extract the count values for both the seabed form and sediment size for each study area. We exported the data to a table format to be further analyzed in R. The seabed form variables are as follows: "Depression", "Mid Flat", "Upper Flat", "Low Slope", "Scarp", "Side Slope", and "Upper Slope" (The Nature Conservancy, 2016a). The sediment types are as follows: "Silt", "Very Fine Sand", "Fine Sand", "Medium Sand", "Coarse Sand", "Very Coarse Sand", and "Gravel/Granule" (The Nature Conservancy, 2016b). The specifications defining sediment size ranges are detailed in **Table 2** and were classified based on grain size according to the Wentworth (Wentworth, 1922) scale.

SEDIMENT CLASS	GRAIN SIZE (mm)
Silt	0.002 - 0.06
Very Fine Sand	0.06 - 0.125
Fine Sand	0.125 - 0.25
Medium Sand	0.25 - 0.5
Coarse Sand	0.5 - 1.0
Very Coarse Sand	1.0 - 2.0
Gravel/Granule	> 2.0

Table 2: Sediment classifications and their corresponding grain size according to the Wentworth (Wentworth, 1922) scale (The Nature Conservancy, 2016b).

One of the analyses conducted was a pairwise Euclidean distance analysis to see which sites are most similar to each other in the distance matrix alone. In order to conduct a pairwise Euclidean distance analysis as well as the multivariate clustering analysis, the categorical seabed forms and sediment type data needed to be converted into a qualitative format. To do this, the relative percent coverage for each category was calculated in R and the tables were pivoted and joined together to show the percent value for each category in each zone **(Appendix A.3 - A.6)**. It was important to make sure the percent coverage areas were relative to the zone they belonged to, as the zone sizes differed significantly between the sites and the sub-regions. Sediment types and seabed forms were edited in separate markdown files, but the process was the same for both.

Each table was brought into R as a data frame and we created a new column in each table called "ZONE-CODE" and populated the cells with the zone code for each study area. We ensured column names and zone codes were the same across all tables to combine them more easily **(Table 3)**.

STUDY AREA NAME	ZONE-CODE
Southern New England	SNE
Empire Wind	EW
Vineyard Wind	VW
New York/New Jersey Bight North	NYNJB_North
New York/New Jersey Bight South	NYNJB_South
Atlantic Shores South	ASH

Table 3: Table of the wind farm study sites and the ZONE-CODEs used for analysis in R.

All processed data (SST, Chlorophyll A concentrations, sea surface height anomalies, wind speeds, depth, bottom temperature, sediment type composition, and seabed form composition) were joined into a single table with six rows **(Appendix A.1.1 - A.1.4)**. The remaining columns included the ZONE-CODE, average wind speeds, average depth, average bottom temperature, percent area for each sediment type and seabed form, as well as the mean and standard deviation for sea surface temperature, chlorophyll A, and sea surface height anomalies for each season **(Table 4)**.

FINAL COLUMN NAMES		
ZONE-CODE	Mean_Depth	Mean_Wind_Speed
Silt	Very.Fine.Sand	Fine.Sand
Medium.Sand	Coarse.Sand	Very.Coarse.Sand
Gravel.Granule	Depression	Mid.Flat
Upper.Flat	Low.Slope	Scarp
Side.Slope	Upper.Slope	Mean_Bottom_Temp
MEAN_mean_sst_fall	STD_mean_sst_fall	MEAN_mean_sst_spr
STD_mean_sst_spr	MEAN_mean_sst_sum	STD_mean_sst_sum
MEAN_mean_sst_wint	STD_mean_sst_wint	MEAN_mean_chlor_fall
STD_mean_chlor_fall	MEAN_mean_chlor_spr	STD_mean_chlor_spr
MEAN_mean_chlor_sum	STD_mean_chlor_sum	MEAN_mean_chlor_wint
STD_mean_chlor_wint	MEAN_mean_sla_fall	STD_mean_sla_fall
MEAN_mean_sla_spr	STD_mean_sla_spr	MEAN_mean_sla_sum
STD_mean_sla_sum	MEAN_mean_sla_wint	STD_mean_sla_wint

Table 4: Final list of variables used for Pairwise Euclidean distance analysis and multivariate clustering analysis.

All NA’s and zeros were replaced with 0.0001 to ensure consistency across the variables, that all observations across each variable are present, and to reduce any statistical bias the NAs would produce. We standardized the data using the “scale” function, which finds the mean of each variable and then subtracts that mean from each measurement. The results were divided by the standard deviation of the variable. At the end of this process, all the measurements were unitless, and we could compare all the variables to each other, which totaled 42 unique variables. We used the standardized data to create a distance matrix and found the pairwise Euclidean distance between the study areas. The data were visualized through a heatmap using R’s ggplot2 package **(Figure 5)**. The analysis was repeated with just the wind farm sites and again with just the larger regions **(Figure 6)**.

The standardized data was additionally exported as a CSV file. The “ZONE-CODE” column was renamed to “NAME”, and the corresponding fields were changed to match the names in the “Covariates_tool_polygon_all.shp” feature class in order to join the tables in ArcPro using the “Join Field” tool. We used the “Multivariate Clustering” tool to analyze this newly joined feature class. We were curious about which primary variables may be driving this clustering, so we re-ran the multivariate clustering and removed a different set of variables each time it was re-run. We first removed sea surface temperature data and kept all others. Next, we brought the SST data back and removed just the Chlorophyll A data. We did the same with wave height anomaly data, and we also ran variations where only benthic habitat data was included (sediment type/seabed forms) and one where it was just oceanographic data.

Duplicates of ArcGIS models and Python/R scripts were made and edited as needed for the new feature class with all 21 sites. We ran through each respective model/script to extract the necessary information. Calculating the sediment type and seabed form percent coverage required splitting up the feature class into a separate shapefile for each individual site. Creating a model for each step was necessary to automate repetitive analysis using iterators. Once all calculations were complete, we exported our Excel sheet with all the values and included the values for the larger subregions (SNE, NYNJB North & NYNJB South). We appended the feature class with all the original covariates “Covariates_tool_polygon_all.shp”, to “All_Sites_Buffered.shp”. Duplicate polygons of VW, EW, and ASH were removed, but the larger subregion polygons were kept. The table with all our newly calculated data was joined to “All_Sites_Buffered.shp”, and the multivariate clustering analysis was conducted.

3. Acquiring and Processing Glider Path Data

Underwater gliders are autonomous, unmanned observing systems that are often used for ocean science. They need little to no human direction while operating and can travel very long distances over long periods, making them uniquely suitable for collecting data in remote areas, safely, and at a relatively low cost (NOAA, n.d.). Gliders can monitor a wide variety of oceanographic variables such as temperature, water currents, salinity, and other ocean conditions.

Through glider data, we can get a more complete understanding of the processes occurring in the ocean (*Underwater Gliders*, n.d.).

As a result, the U.S. Integrated Ocean Observing System (IOOS) office developed a glider data assembly center to coordinate glider operators across the nation and create a centralized location for glider data to be submitted (*Underwater Gliders*, n.d.). For our analysis, we used glider path data from IOOS's Data Assembly Center. The IOOS Glider data was downloaded for all available years (2009 – 2025) as a KML file, which was then converted to a layer format using "arcpy.conversion.KMLToLayer" in Jupyter Notebook.

Additionally, we wanted to look at the overall coverage by the glider paths. However, because glider data is collected at the exact location of the glider and spans across depths within a single trip, we could only measure the path density by comparing the distance traveled to the total area of each zone. We projected the glider polylines to the North American Albers Equal Area Conic coordinate system to match that of the wind farm shapefile. The two feature classes were intersected to determine which glider paths fell into each wind farm area **(Figure 3)**. We calculated the total lengths of the glider polylines in each study area with the Summary Statistics tool. The results were joined to a copy of the wind sites feature class and exported to an Excel sheet where we could calculate the path density **(Table 5)**.

RESULTS

Research Question 1: What kind of data do we have to characterize the regions as well as the immediate area surrounding the wind lease areas?

Through our analysis we wanted to see what the availability of data is amongst our study areas. One method was to map all available IOOS underwater glider path data from 2009 to the present day **(Figure 3)**. This allows us to get a snapshot of where people are focusing their efforts and where there may be gaps. **Figure 3** shows that there has been a lot of activity in the Southern New York/New Jersey Bight subregions, and especially so immediately surrounding the Atlantic Shores South offshore wind farm with a path density of 0.006648 **(Table 5)**. Southern New York/New Jersey Bight has a path density of 0.001937 and is fairly well distributed. Southern New England has the next highest path density of 0.0009 **(Table 5)**, however, it is heavily concentrated to the West and South **(Figure 3)**. This is in direct contrast with Vineyard Wind, which is almost empty of any glider activity. Empire Wind and the Northern New York/New Jersey Bight region are both more haphazardly covered **(Figure 3)**. Because the data was only taken from the IOOS database, there may be additional glider activity that is missing if it has not been uploaded to IOOS.

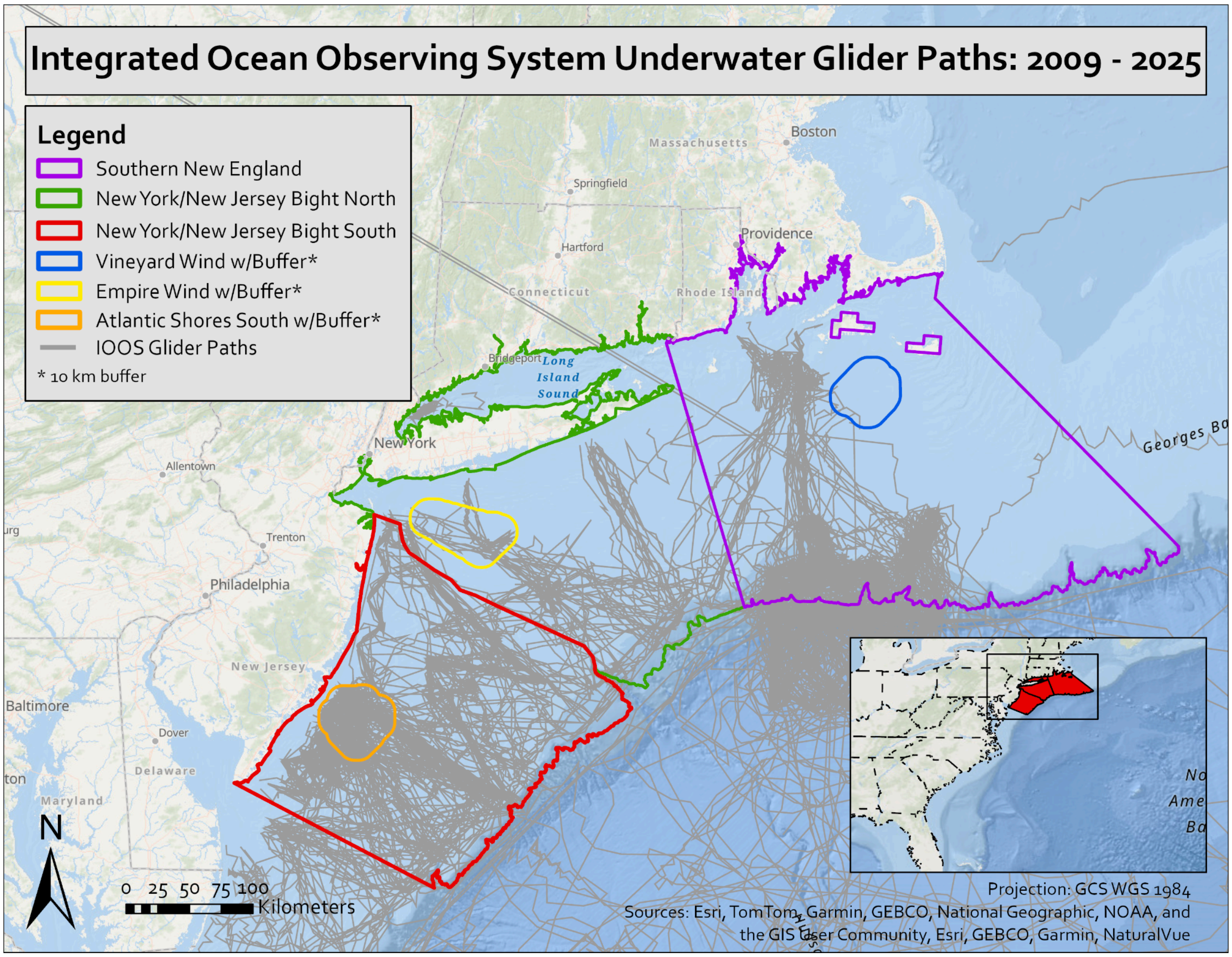


Figure 3: Underwater Glider paths in northeastern US waters taken from the Integrated Ocean Observing System's Data Assembly Center from 2009 to 2025.

ZONE-CODE	Area (km^2)	Glider Path Length (km)	Path Density
ASH	1,590,501.89	10,573.64	0.00664799
EW	1,703,483.40	1,184.04	0.00069507
VW	1,276,886.94	64.55	0.00005056
NYNJB North	26,146,041.98	12,012.95	0.00045945
NYNJB South	25,887,888.04	50,137.93	0.00193673
SNE	39,613,682.00	36,063.70	0.00091038

Table 5: Glider path densities within each offshore wind study area.

The oceanographic data covered the expanse of our study sites and there were no differences found. Average wind speeds did not vary much between the zones, with the southern regions (NYNJB North/EW & NYNJB South/ASH) ranging between 8.73m/s and 8.99m/s. VW and SNE have slightly higher speeds with 9.31m/s and 9.36m/s, respectively. The average depth between all the zones ranged from 25.7 meters (ASH) to 79.0 meters (SNE) **(Table 6)**. For relative sediment type coverage, all of the regions were primarily dominated by "Fine Sand", "Medium Sand", and "Coarse Sand" **(Figure 4, Table 7)**. ASH is 62% 'Medium Sand', followed by 'Coarse Sand' at 32%. EW is 60% 'Medium Sand', followed by 'Coarse Sand' at 23%. For the most part, VW is split evenly between 'Fine Sand' and 'Medium Sand' at 42% for both. NYNJB North is 48% 'Medium Sand' and 19% 'Fine Sand' while NYNJB South is 60% 'Medium Sand' and 20% 'Coarse Sand'. SNE is 34% 'Medium Sand' and 30% 'Fine Sand' **(Table 7)**.

ZONE-CODE	Average Depth (m)	Average Wind Speeds (m/s)	Average Bottom Temperature (℃)
ASH	-25.7	8.74	11.7
EW	-33.5	8.73	10.6
VW	-41.7	9.31	9.6
NYNJB North	-59.5	8.99	10.5
NYNJB South	-61.0	8.89	10.9
SNE	-79.0	9.36	9.8

Table 6: Average depth (m), wind speed (m/s), and bottom temperature (℃) for each offshore wind study zone.

ZONE-CODE	Silt (%)	Very Fine Sand (%)	Fine Sand (%)	Medium Sand (%)	Coarse Sand (%)	Very Coarse Sand (%)	Gravel/ Granule (%)
ASH	0	0.52	5.74	62.60	31.13	0	0
EW	0	0.62	12.66	60.33	22.32	2.94	1.13
VW	3.89	2.50	42.14	42.11	1.02	0	8.33
NYNJB North	7.91	6.19	18.67	47.98	16.18	1.79	1.29
NYNJB South	1.05	2.31	12.18	60.47	19.97	2.55	1.47
SNE	17.51	4.75	29.66	34.28	4.39	1.05	8.36

Table 7: Relative percent coverage of sediment type for each offshore wind study zone.

The predominant seabed form in all of the study zones is “Mid Flat”, followed by “Depression”, and then “Upper Flat” **(Figure 4, Table 8)**. Almost all the zones except for NYNJB South, comprise at least 50% ‘Mid Flat’, with EW peaking at 82% ‘Mid Flat’. Even NYNJB South is still 42% ‘Mid Flat’ with ‘Depression’ as the next highest seabed form coverage **(Table 8)**.

ZONE-CODE	Depression (%)	Mid Flat (%)	Upper Flat (%)	Low Slope (%)	Scarp (%)	Side Slope (%)	Upper Slope (%)
ASH	31.21	49.61	18.61	0.32	0	0.20	0.06
EW	14.24	81.77	3.99	0	0	0	0
VW	30.45	69.27	0.28	0	0	0	0
NYNJB North	29.94	40.82	14.22	2.04	0.18	0.16	3.64
NYNJB South	27.81	42.57	24.31	0.57	1.01	0.07	3.68
SNE	23.07	51.07	17.17	1.56	0.64	0.24	6.25

Table 8: Relative percent coverage of seabed forms for each offshore wind study zone.

The mean bottom temperatures ranged from 9.6 °C for VW, to 11.7 °C for ASH. The temperatures between each wind farm area and its respective subregions were not significantly different **(Table 6)**. The largest temperature difference was between NYNJB South and ASH, with a difference of 0.8 °C. In contrast, the temperature difference between NYNJB North and EW is 0.1 °C and the difference between SNE and VW is 0.2 °C **(Table 6)**.

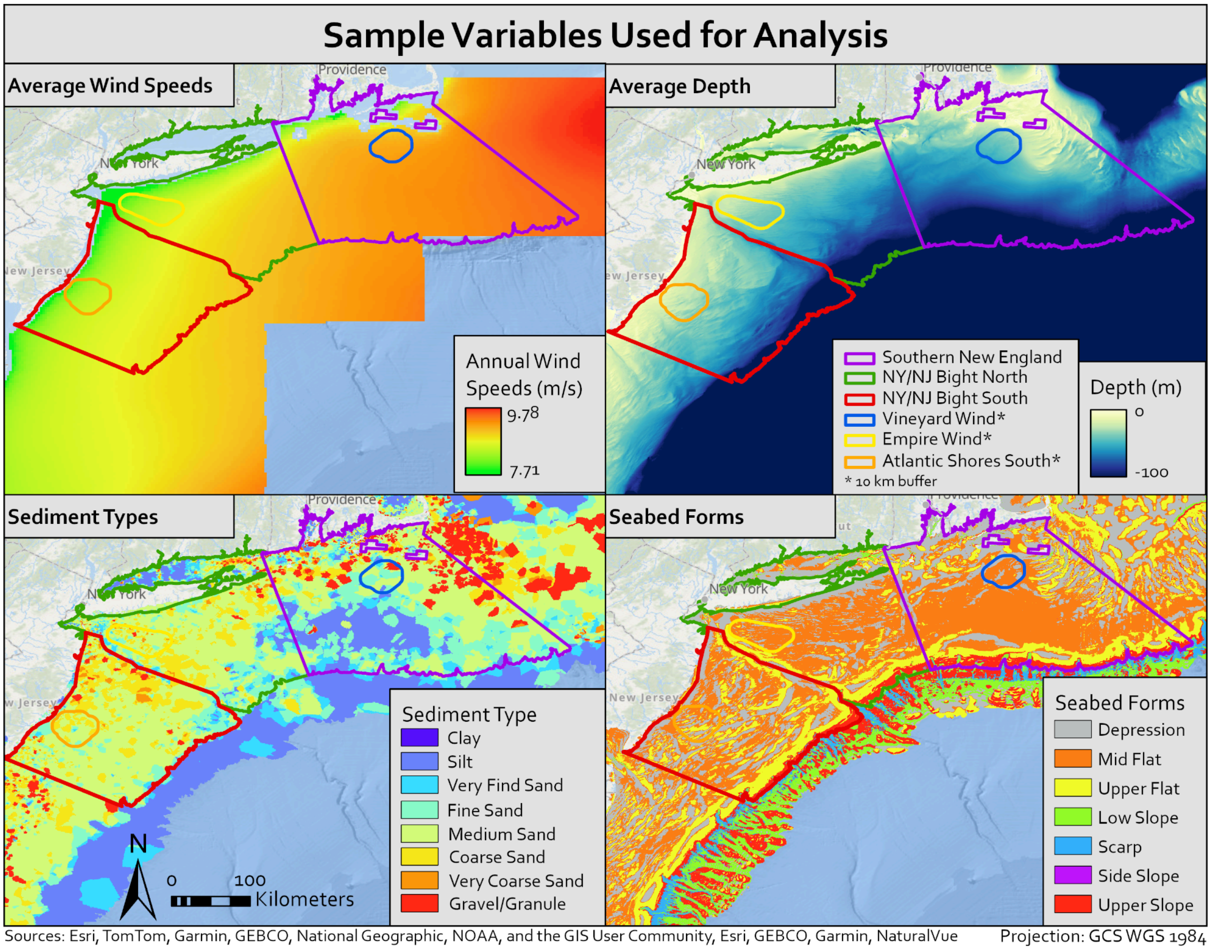


Figure 4: Four maps of the six study areas/zones demonstrating four of the variables used in Pairwise Euclidean Distance analysis and Multivariate Clustering analysis. Map of the average annual wind speeds in meters per second (upper left). Map of the average depth in meters (upper right). Map of the sediment types (lower left). Map of the seabed forms (lower right).

Research Question 2: Are there differences/similarities in available data between sites and regions, i.e., can we extrapolate data from one wind lease area to another?

Our pairwise Euclidean distance analysis showed some interesting results. The variables used for this analysis include sediment type, seabed form, wind speed, depth, sea surface temperatures, bottom temperatures, chlorophyll A concentrations, and wave height anomalies **(Table 4)**. We found that the sub-regions SNE and NYNJB North are more similar to each other than NYNJB North is to NYNJB South **(Figure 5)**. On the other hand, EW and VW are closer to NYNJB South and ASH than they are to the sub-region they fall into **(Figure 5)**. The pairwise

Euclidean distance analysis of just the wind farm sites showed EW and ASH as more similar to each other than either is to VW **(Figure 6)**. Not quite unsurprisingly, VW is calculated to be closer to EW than it is to ASH. In fact, it is completely white, denoting a substantial distance between the two **(Figure 6)**.

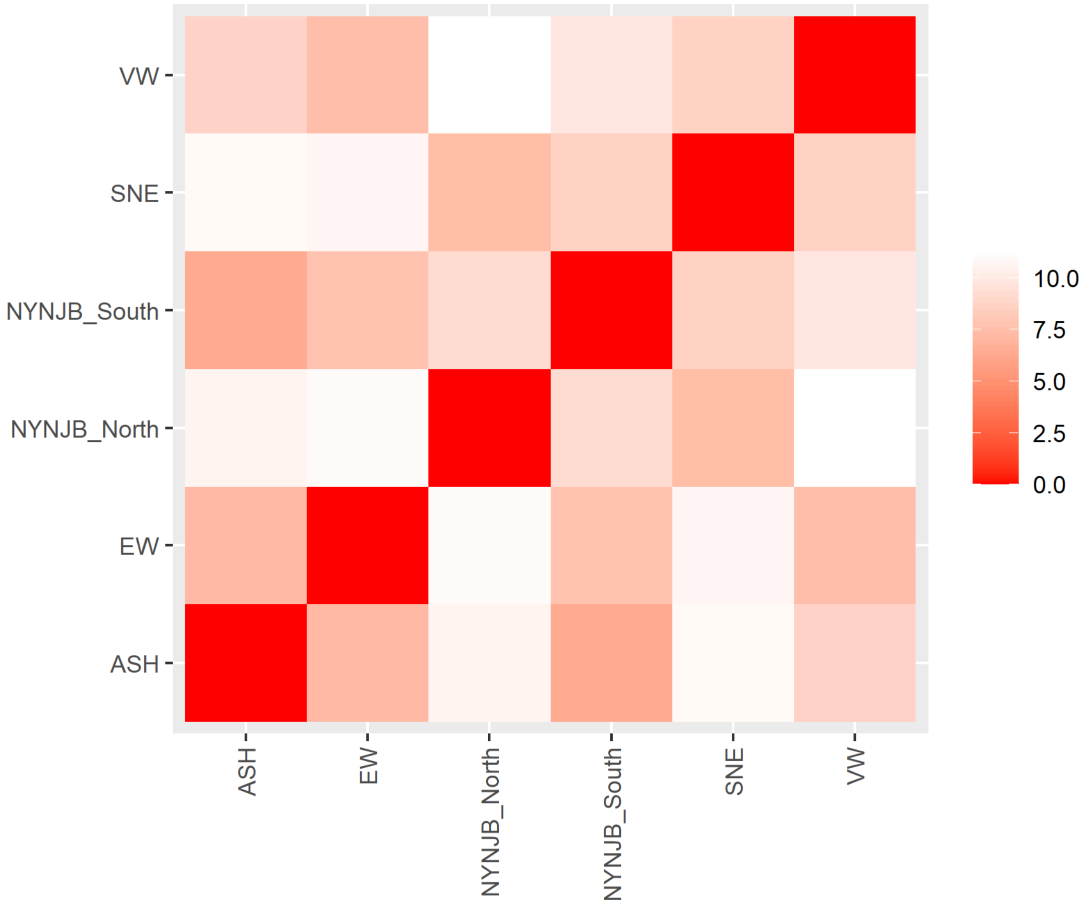


Figure 5: Pairwise Euclidean Distance analysis results as a heatmap for the six study zones: Vineyard Wind (VW), Empire Wind (EW), Atlantic Shores South (ASH), Southern New England (SNE), New York/New Jersey Bight North (NYNJB North), and New York/New Jersey South (NYNJB South).

Figure 6: Pairwise Euclidean Distance analysis results as a heatmap for just the buffered wind farm sites: Vineyard Wind (VW), Empire Wind (EW), and Atlantic Shores South (ASH).

Our multivariate clustering analysis showed similar results to the pairwise Euclidean distance results **(Figure 7)**. This is not surprising as both were conducted with the same data. SNE and NYNJB North were more similar to each other based on every variable, than to NYNJB South. However, neither SNE nor NYNJB North was more similar to their respective offshore wind farm sites. Both EW and VW were more similar to ASH, NYNJB South, and each other than they were to the subregion north of the Hudson Canyon **(Figure 7)**. When re-running the clustering analysis and eliminating individual variables, for the most part, there were no changes except for when we removed just the chlorophyll data, at which point EW and VW created a third cluster **(Figure 8)**.

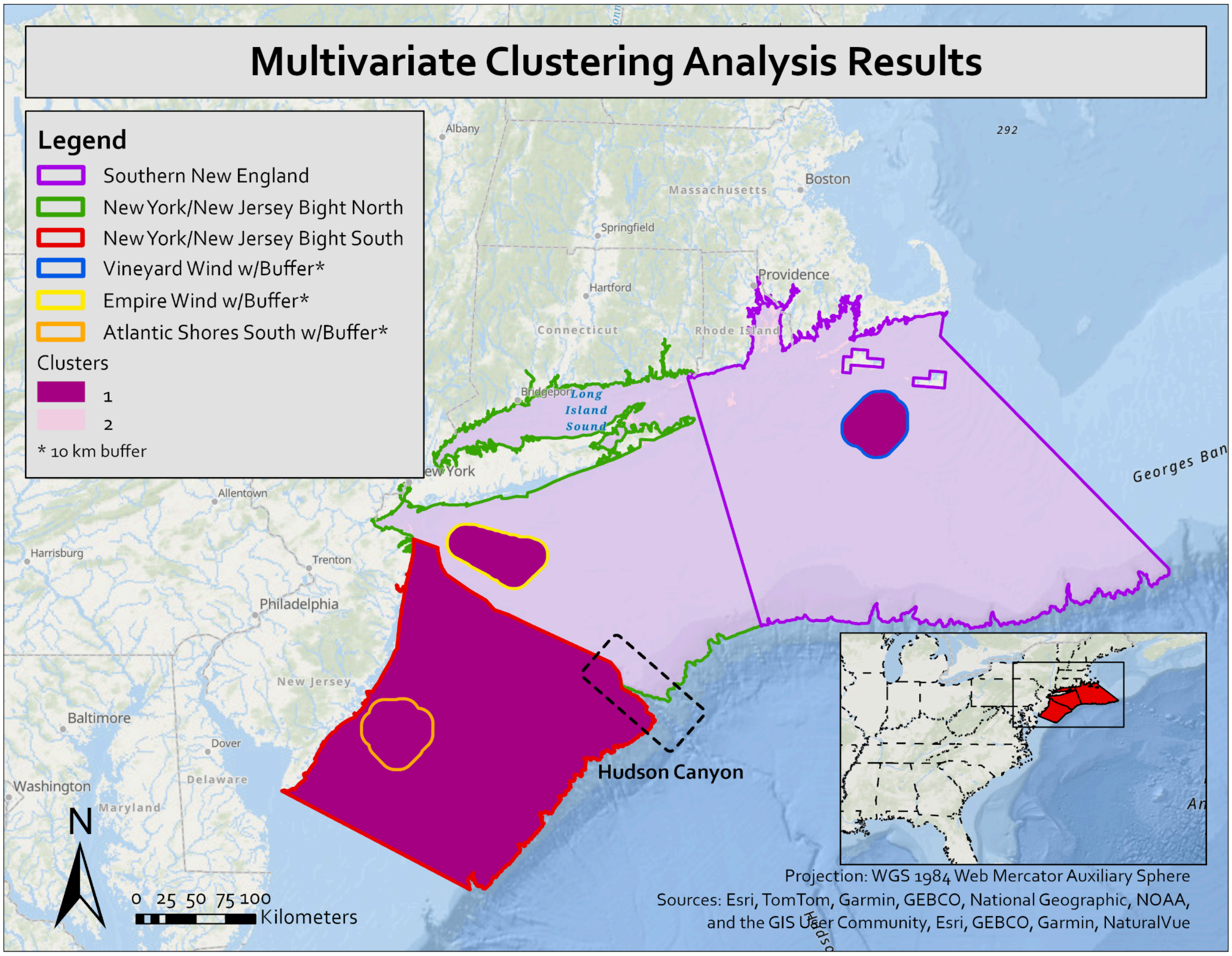


Figure 7: ArcGIS Pro Multivariate Clustering analysis results for the six study zones: Vineyard Wind (VW), Empire Wind (EW), Atlantic Shores South (ASH), Southern New England (SNE), New York/New Jersey Bight North (NYNJB North), and New York/New Jersey South (NYNJB South).

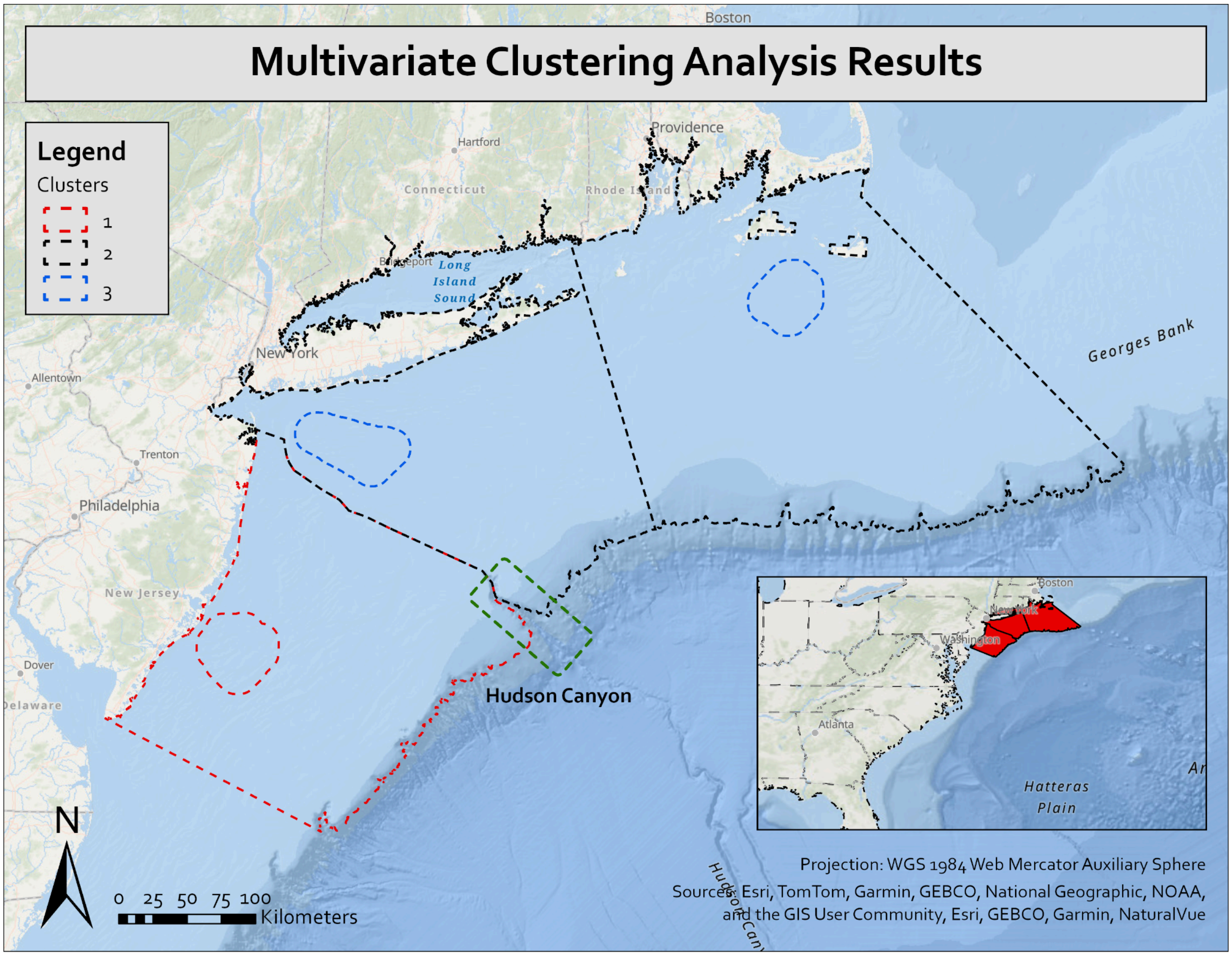


Figure 8: Multivariate Clustering analysis results when Chlorophyll A concentration data is excluded.

Research Question 3. Are the offshore wind farm sites we chose representative of the wind farms in each subregion?

To answer this question, we included an additional 18 offshore wind sites, each with a 10 km buffer, as part of the study area. We calculated the same variables for the added sites: sea surface temperature, chlorophyll A concentration, wave height anomaly, depth, wind speed, bottom temperature, sediment type composition, and seabed form composition. Our results came out to three clusters **(Figure 9)**. This time, VW and EW are still more similar to each other, however, they are no longer as similar to ASH and NYNJB South. Instead, VW and EW are clustered with SNE and NYNJB North. SNE and NYNJB North remain more similar to each other based on our variables than they are to NYNJB South. A new, third cluster appears in the southwest region of NYNJB South, including the site we used for our initial analysis (ASH) **(Figure 9)**. Most of the second cluster surrounds the Hudson Canyon except for one site in SNE that is the sole site in cluster 2, in a sea of sites that belong to cluster 1. Also, despite its close proximity to the Hudson Canyon and two other cluster 2 sites, Empire Wind has been slotted into cluster 1.

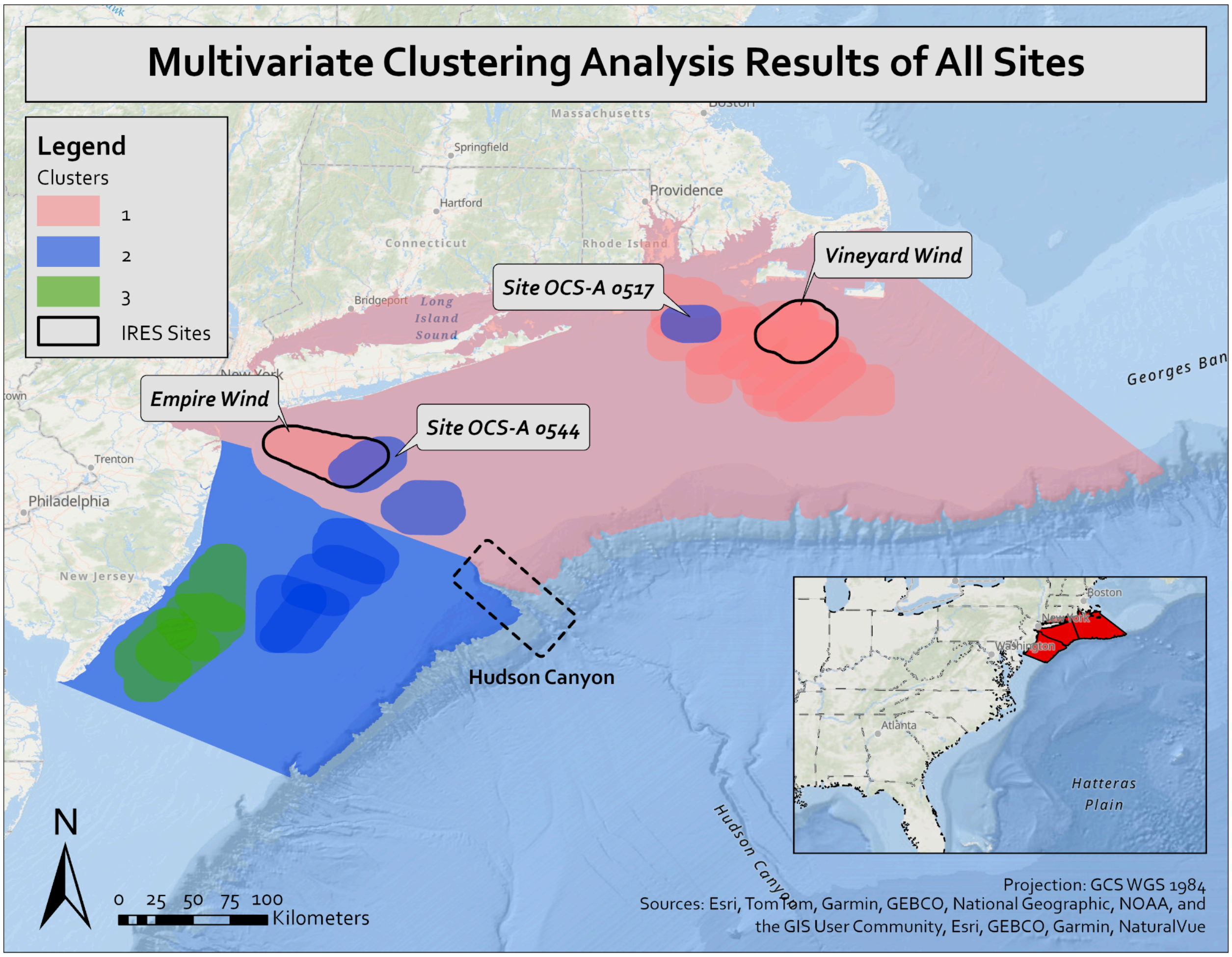


Figure 9: Multivariate Clustering analysis results for all 21 sites and 3 subregions in the study area. Project WOW IRES sites are outlined and labeled. Sites OCS-A 0544 and OCS-A 0517 are also labeled.

DISCUSSION

Through this project, we attempt to use geospatial tools to answer three research questions:

1. What kind of data do we have to characterize the regions as well as the immediate area surrounding the wind lease areas?

2. Are there differences/similarities in available data between sites and regions, i.e., can we extrapolate data from one wind lease area to another?

3. Are the offshore wind farm sites we chose representative of the wind farms in each subregion?

Below we examine the results and evaluate the conclusions that can be drawn. Additionally, we explore future research and analysis needed to build on our understanding of these findings.

Data Availability

To answer this question, we only analyzed glider path data as a sort of proxy for spatial research interest and data availability within the study region. However, it is important to note that this is only one factor and is a relatively new technology that has become more widely used in recent years. The coverage varies widely from region to region and site to site. IOOS records show that a majority of reported gliders have been deployed south of the Hudson Canyon, heavily biasing the NYNJB South subregion and ASH **(Figure 3)**. As we move north, the path density drops off significantly, with a significant lack of glider data in Vineyard Wind and the northern half of Southern New England **(Figure 3)**. This should not be taken as a direct proxy for data availability within the study area, but it exhibits an interesting pattern of increasingly more data collection efforts as we move further south.

As possible further steps, it would be beneficial to make use of data collection via other means, such as research ship tracks or buoy stations. Given more time, incorporating biological variables such as marine wildlife population density data, and benthic community composition data would help to give us a better idea of the data that is currently available and where the gaps are (Bailey et al., 2014). Closing the data gaps is an important step to get a better understanding of the environment surrounding offshore wind areas and examine any impacts from development and operation.

Site and Region Data Comparison

Our Pairwise Euclidean distance and Multivariate Clustering analyses gave us similar results. As mentioned earlier, SNE and NYNJB North were more similar to each other than either was to NYNJB South **(Figure 5, Figure 7)**. This may be due to the Hudson Canyon creating an important divide. SNE was not clustered with its respective wind farm site (VW), and neither was NYNJB North with its corresponding wind farm (EW) **(Figure 7)**. NYNJB South and ASH however, were clustered together along with EW and VW. Instead of each wind farm site matching in similarity with their larger subregion, all of the wind farm sites are more similar to each other and to NYNJB South **(Figure 7)**. It is not entirely surprising that all the wind farm sites were more similar to each other based on our oceanographic variables. After all, wind farm sites are strategically chosen to best fit certain criteria that make them especially ideal for an offshore wind farm, and it stands to reason that because those criteria are often the same regardless of the location, the chosen sites themselves would share many environmental attributes. An interesting question for future research would be to explore why they are also similar to NYNJB South, rather than NYNJB North or SNE, or why the wind farm sites are not creating their own cluster, separate from the larger subregions.

When looking at the Pairwise Euclidean Distance analysis for just the wind farm sites, we do see that ASH and EW are closer to each other than either is to VW **(Figure 6)**. VW is only similar to EW and not ASH, indicating there is some variation amongst the sites themselves, and EW links the two. Interestingly, EW is closer to ASH than it is to VW despite the Hudson Canyon separating the two **(Figure 6)**. This may indicate that the similarities resulting from how wind farm sites are chosen have more weight than the environmental factors of the subregion it resides in, or which side of the Canyon it falls in.

IRES Site Representativeness

The final part of our analysis sought to determine if the sites chosen by Project WOW (i.e., Vineyard Wind and Empire Wind) are suitable representatives for the regions. Many of the wind farm sites are geographically clustered together in NYNJB South, except for site OCS-A 0517 which fell into cluster 2 **(Figure 9)**. ASH and VW both remained more similar to the sites immediately around them. Site OCS-A 0544, which is immediately below EW and overlaps the eastern part of EW, is clustering separately from EW, into cluster 2. As we move further south along the coast, the sites become increasingly different, creating a third cluster that is neither similar to the sites in the northern regions nor to any of the regions themselves **(Figure 9)**. VW and EW clustered together, implying that the initial IRES (Integrated Regional Ecosystem Study) field work is being done in areas with environmentally similar conditions. However, there still needs to be caution when considering extrapolating the data to other sites and especially further south.

CONCLUSION

This project attempted to analyze oceanographic data across multiple scales and characterize offshore wind energy areas along the Northeastern U.S. Atlantic coast. We approached this analysis on three fronts, with three research questions. Each set of results added more to our understanding of the environmental research and conditions of offshore wind energy sites in the NE U.S. Atlantic. For the first research question, we saw a heavy concentration of glider paths in the Southern NY/NJ Bight region. While there were certain hotspots and areas of high concentration in the Northern NY/NJ Bight and Southern New England regions, it was not as distributed in comparison to the Southern Bight region. Similarly, Atlantic Shores South also had more glider activity than Empire Wind and especially Vineyard Wind, which had little to no glider paths crossing the site area. This is only from the glider paths made available via IOOS, and has its limitations. In the future, we would have liked to include other methods of data collection, such as research ship tracks and buoy locations.

Through our multivariate clustering, our findings indicate that the Hudson Canyon is a significant driver separating the Southern NY/NJ Bight region from the Northern N/NJ Bight and Southern New England regions. Additionally, based on the specific oceanographic variables we used, the data shows that the offshore wind farm sites are more environmentally similar to each other than to their respective region. This is not entirely unsurprising, as offshore wind sites are specifically chosen to fit certain environmental conditions. When considering site representation compared to other wind farm sites within the same regions, our results are mixed. On one hand, except for a single site off the coast of Massachusetts (OCS-A 0517), the sites seem to be regionally similar. The Project WOW IRES sites are also similar to the regions they are in, indicating that, at least for now, the initial research conducted in Vineyard Wind and Empire

Wind is in areas with similar environmental conditions. On the other hand, as previously mentioned, there needs to be caution when extrapolating the data to other sites as well as extrapolating further south.

It is important to note that this analysis is a preliminary one with limited variables included. This does not give us any indicator for the magnitude of the clustering or the nuances of which factors are driving the clustering. We have also not ground-truthed any of the remotely sensed satellite data, which adds uncertainty. Caution is also necessary given that as climate change is continuously affecting ocean conditions such as those included in this analysis, the oceanographic conditions of the sites and regions themselves will change and shift (Beaugrand, 2009; Greene et al., 2013; Wang et al., 2004). Meaning the representativeness of the sites suggested by this analysis is subject to change and cannot be presumed static.

The sites we focused on in this analysis have had the most offshore wind development along the U.S. Atlantic coast, and it is important to have a solid understanding of the environmental conditions throughout the development process. In order to minimize effort and disturbance to these areas while also making sure to properly monitor and mitigate impacts, we need to know when research efforts may be redundant or excessive. On the other hand, it is critical to not overshoot in the other direction and not conduct enough research to fully understand these complex dynamics and how they are being impacted by offshore wind development (Miller et al., 2004). It is also important not to incorrectly presume one area is the same as another, resulting in improper management decision-making. This is why knowing when we can or cannot extrapolate research findings is important. It is a precarious balancing act that should not be overlooked. Through this project, we hope to use the power of geospatial analysis to contribute meaningfully to the discussions surrounding responsible offshore wind energy development in the U.S.

ACKNOWLEDGEMENTS

None of this work could have been done without the help of some wonderful people. I would like to thank my advisor, Dr. Patrick Halpin, for his astute expertise and mentorship throughout the process. I learned so much through this opportunity and am grateful to have been able to contribute to such an exciting project. I'd like to thank Jesse Cleary, for his patience and guidance through my many coding obstacles and especially for allowing me to ask for meetings via preemptively scheduling them in his Outlook calendar. I would like to also thank Eliza Carter for generously sharing her data and research, allowing me to expand on her work. I am incredibly thankful for the time she dedicated to giving me invaluable advice, answering my countless questions, and providing thoughtful feedback on my work. Thank you to my roommates, Desa Bolger and Emma Beyer, for the ice-cream runs and movie nights, they got me through the tough times. I'd like to give a huge thank you to my friends and family for your support, none of this would have been possible without you! And finally, I'd like to thank my CaMS cohort for making this such a wonderful last two years.

Reference Code: All R and Python code was done in RStudio and Jupyter Notebook and made available via Github. They can be found HERE.

CITATIONS

Bailey, H., Brookes, K. L., & Thompson, P. M. (2014). Assessing environmental impacts of offshore wind farms: Lessons learned and recommendations for the future. *Aquatic Biosystems*, *10*(1), 8. https://doi.org/10.1186/2046-9063-10-8

Beaugrand, G. (2009). Decadal changes in climate and ecosystems in the North Atlantic Ocean and adjacent seas. *Deep Sea Research Part II: Topical Studies in Oceanography*, *56*(8–10), 656–673. https://doi.org/10.1016/j.dsr2.2008.12.022

BOEM. (2024). *Renewable Energy | Bureau of Ocean Energy Management*. https://www.boem.gov/renewable-energy

Bureau of Ocean Energy Management (BOEM), Baker, K., White, T., & Kilpatrick, T. (2023). *Wildlife and Offshore Wind (WOW): A Systems Approach to Research and Risk Assessment for Offshore Wind Development from Maine to North Carolina (NT-21-x07)*.

Bureau of Ocean Energy Management (BOEM), Office of Renewable Energy Programs (OREP). (2018). *Offshore Wind Leases* (Version 2007) [Dataset].

Costoya, X., deCastro, M., Carvalho, D., & Gómez-Gesteira, M. (2020). On the suitability of offshore wind energy resource in the United States of America for the 21st century. *Applied Energy*, *262*, 114537. https://doi.org/10.1016/j.apenergy.2020.114537

Díaz, H., & Guedes Soares, C. (2020). Review of the current status, technology and future trends of offshore wind farms. *Ocean Engineering*, *209*, 107381. https://doi.org/10.1016/j.oceaneng.2020.107381

Duke University. (n.d.). *Wildlife and Offshore Wind*. Retrieved January 31, 2025, from https://offshorewind.env.duke.edu/

European Commission. (2014). *2030 climate and energy goals for a competitive, secure and* *low-carbon EU economy*.

Greene, C. H., Meyer-Gutbrod, E., Monger, B. C., McGarry, L. P., Pershing, A. J., Belkin, I. M., Fratantoni, P. S., Mountain, D. G., Pickart, R. S., Proshutinsky, A., Ji, R., Bisagni, J. J., Hakkinen, S. M. A., Haidvogel, D. B., Wang, J., Head, E., Smith, P., Reid, P. C., & Conversi, A. (2013). Remote climate forcing of decadal‐scale regime shifts in Northwest Atlantic shelf ecosystems. *Limnology and Oceanography*, *58*(3), 803–816. https://doi.org/10.4319/lo.2013.58.3.0803

Methratta, E. T., Hawkins, A., Hooker, B. R., Lipsky, A., & Hare, J. A. (2020). Offshore Wind Development in the Northeast US Shelf Large Marine Ecosystem. *Oceanography*, *33*(4).

Miller, J. R., Turner, M. G., Smithwick, E. A. H., Dent, C. L., & Stanley, E. H. (2004). Spatial Extrapolation: The Science of Predicting Ecological Patterns and Processes. *BioScience*, *54*(4), 310. https://doi.org/10.1641/0006-3568(2004)054[0310:SETSOP]2.0.CO;2

Mills, A. D., Millstein, D., Jeong, S., Lavin, L., Wiser, R., & Bolinger, M. (2018). Estimating the value of offshore wind along the United States' Eastern Coast. *Environmental Research Letters*, *13*(9), 094013. https://doi.org/10.1088/1748-9326/aada62

National Centers for Coastal Ocean Science (NCCOS). (n.d.). *Offshore Wind Energy*. NCCOS - National Centers for Coastal Ocean Science. Retrieved March 12, 2025, from https://coastalscience.noaa.gov/science-areas/offshore-wind-energy/

National Oceanic and Atmospheric Administration (NOAA). (n.d.). *What is an ocean glider?* Retrieved March 14, 2025, from https://oceanservice.noaa.gov/facts/ocean-gliders.html

National Renewable Energy Laboratory & Bureau of Ocean Energy Mangement, Office of Renewable Energy. (2015). *NREL_HourlyWind_Atlantic_polysandpoints.gdb* [Dataset]. https://metadata.boem.gov/geospatial/NREL_HourlyWind_Atlantic_polysandpoints.xml

NOAA CoastWatch. (n.d.). *Chlorophyll, NOAA S-NPP VIIRS, Science Quality, Global 4km, Level 3, 2012-present, Daily* [Dataset]. https://coastwatch.noaa.gov/erddap/griddap/noaacwNPPVIIRSSQchlaDaily.html

NOAA NESDIS CoastWatch. (n.d.). *Sea Surface Height Anomalies, Altimetry (S-3A/B,CryoSat2,Jason-2/3,SARAL), Near Real-Time, Global 0.25°, 2017-present, Daily* [Dataset]. https://coastwatch.noaa.gov/erddap/griddap/noaacwBLENDEDsshDaily.html

NOAA/National Centers for Environmental Information, The Nature Conservancy. (2020). *Mid-Atlantic Region Bathymetry* [Dataset]. https://portal.midatlanticocean.org/static/data_manager/metadata/html/regional_bathymetry_2021_metadata.htm

Rachel Shmookler & RPS Applied Science Associates (RPS ASA). (2019). *FVCOM Annual Climatology for Temperature, Stratification, and Currents (1978-2013)* [Dataset]. Northeast Regional Ocean Council (NROC) Northeast Ocean Data.

The Nature Conservancy. (2016a). *Seabed Forms*. Northeast Regional Ocean Council (NROC).

The Nature Conservancy. (2016b). *Soft sediments by grain size (in mm)*. Northeast Regional Ocean Council (NROC).

Underwater Gliders. (n.d.). The U.S. Integrated Ocean Observing System (IOOS). Retrieved March 14, 2025, from https://ioos.noaa.gov/project/underwater-gliders/

U.S. Department of Energy. (2023). *Advancing Offshore Wind Energy in the United States*.

Veronica Lance & NOAA/NESDIS/OSPO. (n.d.). *Sea-Surface Temperature, NOAA ACSPO S-NPP VIIRS CoastWatch Co-gridded 4km Daily (degrees C)* [Dataset]. https://coastwatch.noaa.gov/erddap/griddap/noaacwL3CollatednppC.html

Wang, X. L., Zwiers, F. W., & Swail, V. R. (2004). North Atlantic Ocean Wave Climate Change

Scenarios for the Twenty-First Century. *Journal of Climate*, *17*(12), 2368–2383. https://doi.org/10.1175/1520-0442(2004)017<2368:NAOWCC>2.0.CO;2

Watson, S. C. L., Somerfield, P. J., Lemasson, A. J., Knights, A. M., Edwards-Jones, A., Nunes, J., Pascoe, C., McNeill, C. L., Schratzberger, M., Thompson, M. S. A., Couce, E., Szostek, C. L., Baxter, H., & Beaumont, N. J. (2024). The global impact of offshore wind farms on ecosystem services. *Ocean & Coastal Management*, *249*, 107023. https://doi.org/10.1016/j.ocecoaman.2024.107023

Wentworth, C. K. (1922). A Scale of Grade and Class Terms for Clastic Sediments. *The Journal of Geology*, *30*(5), 377–392. https://doi.org/10.1086/622910

APPENDIX

A.1 Oceanographic Data for the 3 Primary Wind Farm Sites and 3 Subregions: Used for Pairwise Euclidean Distance and Multivariate Clustering Analysis

A.1.1

NAME	Mean_Depth	Mean_Wind_ Speed	Silt	Very.Fine .Sand	Fine.Sand	Medium.Sand	Coarse.Sand	Very.Coarse. Sand	Gravel.Granule	Depression	Mid.Flat
Atlantic Shores South	1.224356094	-0.964823697	-0.74335933	-1.01337	-1.073667332	0.97063631	1.348021446	-1.105294462	-0.89227834	0.780528307	-0.518998816
Empire Wind	0.829816551	-0.988859054	-0.74335933	-0.972268	-0.558926071	0.775737544	0.571814547	1.233716647	-0.598794233	-1.822055953	1.636671767
NYNJB North	-0.470856527	-0.058507928	0.418098428	1.492466	-0.11210413	-0.284869694	0.030646268	0.317750626	-0.557822115	0.586181064	-0.504583007
NYNJB South	-0.549019314	-0.400868175	-0.588671462	-0.222271	-0.594986499	0.787353123	0.363985887	0.928061203	-0.509999302	0.259332599	-0.990897723
Southern New England	-1.453722914	1.295208682	1.828692233	0.855209	0.705512849	-1.460837017	-1.008809041	-0.268939551	1.284487176	-0.468038629	-0.421052704
Vineyard Wind 1 Offshore Wind Project	0.41942611	1.117850172	-0.171400538	-0.139766	1.634171183	-0.788020267	-1.305659107	-1.105294462	1.274406814	0.664052612	0.798860483

A.1.2

NAME	Upper.Flat	Low.Slope	Scarp	Side.Slope	Upper.Slope	Mean_Bottom _Temp	MEAN_mean _sst_fall	STD_mean _sst_fall	MEAN_mean _sst_spr	STD_mean _sst_spr	MEAN_mean _sst_sum
Atlantic Shores South	0.600855401	-0.501307164	-0.719566168	0.843099345	-0.837784805	1.557592227	0.813186091	-0.8241687	0.956324494	-0.9623215	0.884132072
Empire Wind	-0.992415912	-0.872706744	-0.719566168	-1.067078348	-0.859573649	0.121154002	0.169614969	-0.8673441	0.178078412	-0.7929098	0.445777231
NYNJB North	0.122327066	1.511274664	-0.290540245	0.45584973	0.517863912	-0.040746295	0.325424053	0.35304177	0.006796944	0.84327794	0.174401763
NYNJB South	1.221489268	-0.211528894	1.650574024	-0.435416188	0.533067074	0.495124887	1.082865658	0.17778602	1.117949208	0.69014718	0.915925421
Southern New England	0.444113342	0.946974881	0.798664726	1.270623808	1.506001118	-0.929981851	-0.90160427	1.75051749	-0.77461138	1.16759879	-0.87733794
Vineyard Wind 1 Offshore Wind Project	-1.396369164	-0.872706744	-0.719566168	-1.067078348	-0.859573649	-1.20314297	-1.4894865	-0.5898325	-1.48453768	-0.9457926	-1.54289855

A.1.3

NAME	MEAN_mean _sst_wint	STD_mean _sst_wint	MEAN_mean _chlor_fall	STD_mean _chlor_fall	MEAN_mean _chlor_spr	STD_mean _chlor_spr	MEAN_mean _chlor_sum	STD_mean_ chlor_sum	MEAN_mean _chlor_wint	STD_mean_ chlor_wint	MEAN_mean _sla_fall
Atlantic Shores South	-0.37957845	-0.8359566	0.016827183	-0.5424818	0.393019211	-0.5807306	-0.32815063	-0.57661341	-0.26773112	-0.6068486	-0.91587903
Empire Wind	-0.0897559	-0.9553294	-0.9772667	-0.7407627	-0.3006505	-0.6181311	-0.4296254	-0.72494836	-0.94339238	-0.8067971	1.636271445
NYNJB North	0.207422485	0.81560338	1.523031082	1.68431282	1.792030677	1.84861493	1.935304767	1.78226347	1.691150122	1.61490375	0.659227402
NYNJB South	1.736353211	0.89034705	-1.20427119	0.21755346	-1.10563164	0.04044883	-0.68501889	-0.1470312	-0.99819569	0.25303663	-0.94405067
Southern New England	-0.14437631	1.02423655	0.135236085	0.42601164	-0.29422532	0.21322825	0.184906752	0.49957964	0.10465349	0.5492803	-0.39542
Vineyard Wind 1 Offshore Wind Project	-1.33006504	-0.938901	0.506443544	-1.0446335	-0.48454242	-0.9034303	-0.6774166	-0.83325013	0.413515579	-1.0035749	-0.04014915

A.1.4

NAME	MEAN_mean _sla_fall	STD_mean _sla_fall	MEAN_mean _sla_spr	STD_mean _sla_spr	MEAN_mean _sla_sum	STD_mean _sla_sum	MEAN_mean _sla_wint	STD_mean _sla_wint
Atlantic Shores South	-0.91587903	-1.1707519	-1.43190079	-1.1668629	-1.36223384	-1.0779643	-1.70082551	-1.1692599
Empire Wind	1.636271445	-0.6359666	0.479772847	-0.6282579	1.466460672	-0.6152782	0.283270663	-0.6449177
NYNJB North	0.659227402	1.51743886	0.778331026	1.57546842	0.802051403	1.67564304	0.760534965	1.43223916
NYNJB South	-0.94405067	0.39512288	-1.12290773	0.33482141	-0.52517575	0.14525816	-0.64365603	0.54735722
Southern New England	-0.39542	0.56373969	0.72592723	0.50937445	-0.15817464	0.49402272	0.95722954	0.57010064
Vineyard Wind 1 Offshore Wind Project	-0.04014915	-0.669583	0.570777412	-0.6245435	-0.22292784	-0.6216815	0.343446369	-0.7355195

A.2 Oceanographic Data for All 21 Wind Farm Sites and 3 Subregions: Used for Pairwise Euclidean Distance and Multivariate Clustering Analysis

A.2.1

NAME	MEAN_depth	MEAN_wind	Silt	Very.Fine.Sand	Fine.Sand	Medium.Sand	Coarse.Sand	Very.Coarse.Sand	Gravel.Granule	Depression	Mid.Flat
OCS-A 0486	0.463264663	0.211380369	-0.17187793	0.0451766	0.029325111	-0.735952237	-0.07162595	0.704239108	2.162437424	1.30466733	-1.235595947
OCS-A 0487	-0.534546212	0.80298512	-0.276730668	-0.16057	0.348395704	-0.794957053	-0.23077432	-0.089248565	2.530300259	0.552218547	-0.450994727
OCS-A 0498	1.50300217	-1.188828166	-0.571337453	-0.504062	-0.415510959	1.248008187	-0.263446785	-0.487874466	-0.643854906	0.813531159	-0.926253669
OCS-A 0500	-0.75609349	0.911783079	0.278118014	0.3643137	1.25816229	-0.719883514	-0.951709145	-0.5525749	0.875240908	-0.036665762	0.452562859
OCS-A 0517	0.204630087	0.616132006	-0.571337453	-0.728646	-0.559320584	-0.662119132	1.099262491	0.075486623	1.770230934	0.328153757	-1.087015977
OCS-A 0520	-0.967619223	1.155741841	1.759468735	2.15431	0.913950901	-0.750157305	-1.037137851	-0.560163932	-0.643854906	-0.742705437	1.032068632
OCS-A 0521	-0.952865567	1.237932994	3.022253778	2.1231351	0.945608192	-1.307272459	-1.037137851	-0.560163932	-0.643854906	-1.531158056	1.392315961
OCS-A 0522	-0.826594606	1.32144082	1.889608385	-0.246443	1.475431583	-1.118040425	-1.037137851	-0.560163932	-0.061831446	-1.817232621	1.374040971
OCS-A 0532	1.854501012	-1.476944719	-0.571337453	-0.349523	-0.311425138	0.877723966	-0.115268929	-0.176267492	-0.461279287	1.010247433	-0.896317019
OCS-A 0537	-1.423825284	-0.065306143	-0.571337453	-0.728646	-1.100609144	-0.213354114	2.136050252	-0.224165187	-0.643854906	-0.994777692	0.616710179
OCS-A 0538	-0.718420794	-0.360076117	-0.557130267	-0.32556	-0.922607696	-1.074299058	1.954681618	3.183805035	-0.160246954	-0.331236937	-0.530520442
OCS-A 0539	-0.072087696	-0.423450878	-0.571337453	-0.728646	-0.969091905	0.692759843	0.412622357	2.399634065	-0.643854906	0.452461559	-0.918906277
OCS-A 0541	0.238370951	-0.597910437	-0.571337453	-0.728646	-0.969447545	1.777013088	-0.237932135	-0.436927739	-0.643854906	1.061417947	-1.293862377
OCS-A 0542	-0.332241753	-0.455961393	-0.571337453	-0.728646	-0.910954775	1.946666966	-0.469489183	-0.560163932	-0.643854906	1.119928874	-1.274144111
OCS-A 0544	-0.034353234	-0.661694459	-0.571337453	-0.728646	-0.890864361	0.847672415	0.73123983	-0.393282292	-0.643854906	-1.543146371	1.479687751
OCS-A 0549	1.739935357	-1.512659058	-0.56397992	-0.685913	-0.906221269	0.097362834	1.257998258	0.255429016	-0.105871206	1.000839749	-0.117524947
OCS-A 0534	-0.433983462	1.002093503	0.188912994	0.8310102	1.148380083	-0.246466552	-1.009977686	-0.560163932	-0.221725779	0.12779924	0.57881643
OCS-A 0561	-1.288682749	1.087041304	0.268919089	2.2716966	2.029213199	-1.193387763	-1.037137851	-0.560163932	-0.643854906	-0.919673068	1.11080345
OCS-A 0499	1.563125673	-1.257033602	-0.571337453	-0.578951	-0.805686416	0.810360185	0.687655468	-0.560163932	-0.643854906	0.675047702	-0.719799771
OCS-A 0501	-0.015078594	0.935672738	-0.124187684	-0.014359	1.06361748	-0.182055991	-0.980462378	-0.560163932	0.588255944	0.594522631	0.362830663
OCS-A 0512	0.78956275	-1.282338802	-0.571337453	-0.552388	-0.450344752	0.700378117	0.199727642	0.223058254	-0.476961737	-1.124239983	1.051098368
NYNJB North	-0.470856527	-0.058507928	0.418098428	1.4924658	-0.11210413	-0.284869694	0.030646268	0.317750626	-0.557822115	0.586181064	-0.504583007
NYNJB South	-0.549019314	-0.400868175	-0.588671462	-0.222271	-0.594986499	0.787353123	0.363985887	0.928061203	-0.509999302	0.259332599	-0.990897723
Southern New England	-1.453722914	1.295208682	1.828692233	0.8552091	0.705512849	-1.460837017	-1.008809041	-0.268939551	1.284487176	-0.468038629	-0.421052704

A.2.2

NAME	Upper.Flat	Low.Slope	Scarp	Side.Slope	Upper.Slope	MEAN_bottom_temp	MEAN_mean_sst_fall	STD_mean_sst_fall	MEAN_mean_sst_spr	STD_mean_sst_spr	MEAN_mean_sst_sum
OCS-A 0486	0.932896105	1.278148209	1.00E-04	-0.177144626	1.361951015	-0.196613888	-0.8336855	-0.0947146	-0.80492225	1.66978834	-0.9265689
OCS-A 0487	0.259250338	1.62212828	1.00E-04	-0.3932403	-0.594283005	-0.803069403	-0.7344809	0.09706761	-0.7799079	0.27090001	-0.72872446
OCS-A 0498	0.83276435	0.636902503	1.00E-04	2.675288147	1.229808301	1.740728881	1.230751966	-0.6849902	1.245740425	-0.5060038	0.927160474
OCS-A 0500	-0.728183482	-0.658154829	1.00E-04	-0.569433646	-0.694992998	-0.897858994	-0.78589351	1.26383238	-0.94765008	2.09104576	-0.90582268
OCS-A 0517	1.531447417	3.046215222	1.00E-04	-0.569433646	-0.405358845	-0.364541198	-0.78124509	-0.7347123	-0.66973465	-1.6160213	-0.75642509
OCS-A 0520	-1.09574691	-0.658154829	1.00E-04	-0.569433646	-0.694992998	-0.95852819	-1.01685188	1.48931882	-1.13292749	0.11945843	-0.96022891
OCS-A 0521	-1.010931748	-0.658154829	1.00E-04	-0.569433646	-0.694992998	-0.907649773	-1.18097681	2.06709349	-1.16144605	0.56787197	-1.08230388
OCS-A 0522	-0.731113356	-0.658154829	1.00E-04	-0.506512396	0.629790642	-0.994422525	-1.41760593	2.15387233	-1.1298363	0.56124341	-1.31586308
OCS-A 0532	0.617833764	0.203153211	1.00E-04	1.973494395	1.189603454	1.996923472	1.162785659	-0.2144574	1.361092893	0.66616281	0.775192382
OCS-A 0537	-0.152766747	-0.658154829	1.00E-04	-0.569433646	-0.694992998	-0.228975063	0.768149521	-0.8058895	0.673781585	-1.291457	0.712864197
OCS-A 0538	1.210426131	0.299947487	1.00E-04	-0.097705705	-0.458068404	-0.150230495	0.909029614	-0.7722685	0.808474777	-0.3078447	0.996430692
OCS-A 0539	1.161919177	-0.037640849	1.00E-04	0.423946979	2.870122874	0.111615836	0.997449404	-0.8154952	0.929891219	0.03822437	1.107166368
OCS-A 0541	1.291930625	-0.46822397	1.00E-04	0.029579561	-0.194393123	0.451305915	1.027448207	-0.9524582	0.995831976	-0.6958581	1.208104503
OCS-A 0542	1.197970689	-0.411148218	1.00E-04	-0.058756082	1.008292004	0.228704162	1.01971367	-0.9741985	1.053612856	0.14376197	1.210247985
OCS-A 0544	-1.151017487	-0.658154829	1.00E-04	-0.569433646	-0.694992998	-0.100285367	0.484172082	-0.9884929	0.344970501	-1.0376275	0.5494904
OCS-A 0549	-0.677811968	-0.539773325	1.00E-04	-0.391801078	-0.627844784	1.684067047	0.838104667	-0.4032888	1.000351198	-0.5848237	0.885904421
OCS-A 0534	-1.093552257	-0.658154829	1.00E-04	-0.569433646	-0.694992998	-0.861727541	-1.11215243	0.75310048	-1.12242322	-0.0489003	-1.1691461
OCS-A 0561	-1.073046206	-0.658154829	1.00E-04	-0.569433646	-0.694992998	-1.185491944	-0.70946877	0.23064626	-0.96704064	-1.3970822	-0.70032482
OCS-A 0499	0.603380051	0.951839742	1.00E-04	2.217187567	0.24531685	1.634668255	1.06446435	-0.427678	1.094058329	-0.2964443	1.010068695
OCS-A 0501	-1.139032025	-0.658154829	1.00E-04	-0.569433646	-0.694992998	-0.64641627	-1.3260506	0.39250576	-1.16552766	-0.0967461	-1.41016388
OCS-A 0512	-0.786616459	-0.658154829	1.00E-04	-0.569433646	-0.694992998	0.447797084	0.396342273	-0.5787932	0.373610464	1.75035197	0.572941678
NYNJB North	0.122327066	1.511274664	-0.290540245	0.45584973	0.517863912	-0.040746295	0.325424053	0.35304177	0.006796944	0.84327794	0.174401763
NYNJB South	1.221489268	-0.211528894	1.650574024	-0.435416188	0.533067074	0.495124887	1.082865658	0.17778602	1.117949208	0.69014718	0.915925421
Southern New England	0.444113342	0.946974881	0.798664726	1.270623808	1.506001118	-0.929981851	-0.90160427	1.75051749	-0.77461138	1.16759879	-0.87733794

A.2.3

NAME	STD_mean _sst_sum	MEAN_mean _sst_wint	STD_mean _sst_wint	MEAN_mean _chlor_fall	STD_mean _chlor_fall	MEAN_mean _chlor_spr	STD_mean _chlor_spr	MEAN_mean _chlor_sum	STD_mean_ chlor_sum	MEAN_mean _chlor_wint	STD_mean_ chlor_wint
OCS-A 0486	-0.0225167	-0.81537829	0.47425121	1.222913337	1.0323183	-0.025525	-0.4801639	1.296408359	0.37115194	1.070809166	-0.1834677
OCS-A 0487	0.11083174	-0.17638178	-0.3418385	-0.21993266	-0.4098349	-0.56917572	-0.7951641	-0.16183667	-0.37355531	-0.10636922	-0.95702735
OCS-A 0498	-0.35567	-0.22534218	0.62250543	0.465521113	0.30247427	0.886746779	0.14272452	0.25215258	-0.14939125	0.565040346	0.603033624
OCS-A 0500	1.02917188	-0.52299602	1.42021698	0.04213296	0.05660817	-0.28056193	-0.0504196	-0.38342763	-0.09591102	0.34530696	0.649061087
OCS-A 0517	-0.7940818	-0.4245567	-1.400725	0.220097447	-0.6243585	-0.4097322	-1.0395315	0.478538365	-0.60086393	0.308242718	-1.09467292
OCS-A 0520	1.43898632	-0.59197221	0.53375133	0.366718969	0.08330378	0.164804378	0.33794507	-0.84464287	-0.24942021	0.483382008	0.567680413
OCS-A 0521	1.91385681	-0.67280192	0.5527954	0.494032974	0.47986929	0.421474067	0.85828086	-0.67780809	0.09544045	0.32540736	0.352994256
OCS-A 0522	2.16994476	-0.76580595	0.37314533	0.375812222	0.41114246	0.618647598	1.03127001	-0.58480402	0.10923811	0.348459439	-0.07598672
OCS-A 0532	-0.1160868	-0.69744833	1.4940449	1.632415052	1.73557395	1.680043773	1.4137053	1.610168649	2.01603739	1.534067941	2.080368991
OCS-A 0537	-1.0132454	1.975093979	-2.0248813	-1.60884442	-1.0690938	-1.53772893	-1.2782537	-0.89280269	-0.78915283	-1.24744099	0.030501799
OCS-A 0538	-0.995993	1.695234246	-1.0870255	-1.44476838	-1.1430491	-1.30144737	-0.999382	-0.707944	-0.85817283	-1.44797421	-0.92329499
OCS-A 0539	-1.0464342	1.508904027	-0.9401384	-1.33447508	-1.1967137	-1.22959562	-0.9263944	-0.91762585	-0.91828782	-1.04172113	-1.15832933
OCS-A 0541	-1.0370966	1.203702187	-0.8890383	-1.16678334	-1.12131	-0.90635043	-0.7391812	-0.95222602	-0.97265557	-1.50315692	-1.13009077
OCS-A 0542	-1.1003673	1.683194953	-1.0030651	-1.38041037	-1.2590118	-1.23318469	-1.0191598	-1.03702047	-1.01164383	-1.71613555	-0.95187067
OCS-A 0544	-0.7591664	0.610027229	-0.5510002	-1.05979334	-0.7856536	-0.64926548	-0.643746	0.137664045	-0.52720083	-1.41703536	-1.19860314
OCS-A 0549	-0.2674255	-0.8308455	0.70331462	1.309809273	2.15216085	2.052732882	2.23487208	2.478383442	2.75558536	1.049133109	1.940836163
OCS-A 0534	0.90007622	-0.84407539	0.65864962	0.65483813	-0.0120405	0.177678779	0.03861373	-0.27836455	-0.08668168	0.824195399	-0.0868714
OCS-A 0561	0.06422272	-0.16599616	-1.0222858	-0.35740848	-0.7000363	-0.41827969	-0.7158716	-1.07092125	-0.77337701	-0.06413196	-0.28768195
OCS-A 0499	-0.2991471	-0.47286433	1.09719111	0.738468055	1.33374757	1.288104023	1.31107763	1.187052298	1.47061712	0.56156311	1.477934771
OCS-A 0501	0.70137421	-1.22668167	0.69699862	1.153160589	-0.0524763	0.558906154	0.14307155	0.175808166	-0.02050882	1.199648516	-0.25769715
OCS-A 0512	-0.5212339	-0.24301021	0.63313362	-0.10350404	0.78637979	0.711708639	1.17570701	0.893248198	0.60875256	-0.07129073	0.603182969
NYNJB North	0.28757761	0.207422485	0.81560338	1.523031082	1.68431282	1.792030677	1.84861493	1.935304767	1.78226347	1.691150122	1.614903754
NYNJB South	-0.204839	1.736353211	0.89034705	-1.20427119	0.21755346	-1.10563164	0.04044883	-0.68501889	-0.1470312	-0.99819569	0.253036631
Southern New England	1.86266998	-0.14437631	1.02423655	0.135236085	0.42601164	-0.29422532	0.21322825	0.184906752	0.49957964	0.10465349	0.549280297

A.2.4

NAME	MEAN_mean _sla_fall	STD_mean _sla_fall	MEAN_mean _sla_spr	STD_mean _sla_spr	MEAN_mean _sla_sum	STD_mean _sla_sum	MEAN_mean _sla_wint	STD_mean _sla_wint
OCS-A 0486	-0.27975369	1.3809372	0.721689547	1.2793384	1.217122237	1.62036602	0.455589165	1.1420614
OCS-A 0487	0.151325561	1.86201591	0.974629613	1.44372292	0.533446876	2.00782156	0.823786003	1.54970391
OCS-A 0498	-0.51207659	0.0275832	-1.33428267	-0.0334132	-1.29005308	-0.1141848	-1.62339631	0.44627225
OCS-A 0500	0.351454242	0.5626244	0.969987802	0.16464513	0.483493256	0.67453258	0.797675785	0.16399107
OCS-A 0517	-0.03505828	-1.516687	0.914374791	-1.5455694	1.155271814	-1.4424005	0.642895619	-1.5166299
OCS-A 0520	0.342178733	0.26553677	0.956021643	0.40263426	-0.21663372	0.31945409	0.883687539	0.51008409
OCS-A 0521	0.232249517	0.75825273	0.794235045	1.1247271	-0.37104759	0.81783096	0.817062006	1.06338259
OCS-A 0522	0.354791023	-1.516687	0.941552502	-1.5455694	-0.51525085	-1.4424005	1.001390607	-1.5166299
OCS-A 0532	-0.51207659	0.0275832	-1.33428267	-0.0334132	-1.29005308	-0.1141848	-1.62339631	0.44627225
OCS-A 0537	0.676206347	-0.0546871	0.208256879	-0.1590186	1.114148432	-0.0537772	0.667396245	-0.0358552
OCS-A 0538	-0.17101833	0.85831455	-0.38867676	1.06396398	0.430817802	0.53733032	0.040089562	1.26318332
OCS-A 0539	-0.84431323	-0.2098979	-1.00863817	-0.2153639	-0.26460783	-0.2789544	-0.48267633	-0.1992065
OCS-A 0541	-1.26722401	0.75396548	-1.32955577	0.52502637	-0.88038227	0.68236442	-0.98023685	1.05121769
OCS-A 0542	-1.73625246	-0.2688434	-1.44989531	-0.0951617	-0.76047492	-0.4107986	-0.42829877	-0.2031281
OCS-A 0544	2.216669921	0.21046306	0.340091759	0.29747519	1.798823769	0.11105331	0.411261068	-0.0751537
OCS-A 0549	-0.97531914	-1.516687	-1.18520464	-1.5455694	-1.1226864	-1.4424005	-1.86390252	-1.5166299
OCS-A 0534	0.305260161	-1.516687	0.735700067	-1.5455694	-0.17608124	-1.4424005	0.519616233	-1.5166299
OCS-A 0561	0.327163354	0.35216996	1.14587371	0.54616859	-0.10124678	0.4060886	1.126060467	-0.0494887
OCS-A 0499	-1.12207512	-1.516687	-1.42119371	-1.5455694	-1.45285263	-1.4424005	-1.77733841	-1.5166299
OCS-A 0501	0.089381267	0.46233603	0.416409822	0.71600294	-0.12807898	0.489971	0.327344582	0.08738
OCS-A 0512	2.408487295	0.59508103	0.332906498	0.70051299	1.836325168	0.51708927	0.265390611	0.42243317
NYNJB North	0.659227402	1.51743886	0.778331026	1.57546842	0.802051403	1.67564304	0.760534965	1.43223916
NYNJB South	-0.94405067	0.39512288	-1.12290773	0.33482141	-0.52517575	0.14525816	-0.64365603	0.54735722
Southern New England	-0.39542	0.56373969	0.72592723	0.50937445	-0.15817464	0.49402272	0.95722954	0.57010064

A.3 Seabed Form Relative Percent Coverage for the 6 Primary Study Areas

ZONE-CODE	Depression	Mid Flat	Upper Flat	Low Slope	Scarp	Side Slope	Upper Slope
ASH	31.20808593	49.60768	18.612248	0.31769823	0	0.196639829	0.057646855
EW	14.242147	81.76811	3.98973862	0	0	0	0
NYNJB NORTH	29.94115924	49.82275	14.2204756	2.03873522	0.182012	0.156795382	3.638071832
NYNJB SOUTH	27.81047276	42.56742	24.3082174	0.56549889	1.005069	0.065092264	3.67822514
SNE	23.06882577	51.06894	17.173722	1.55618053	0.643849	0.240628189	6.247856424
VW	30.44879465	69.26881	0.28239123	0	0	0	0

A.4 Sediment Types by Grain Size (in mm) Relative Percent Coverage for the 6 Primary Study Areas

ZONE-CODE	Silt	Very Fine Sand	Fine Sand	Medium Sand	Coarse Sand	Very Coarse Sand	Gravel/Granule
ASH	0	0.524156791	5.742935278	62.60255242	31.13035552	0	0
EW	0	0.617152586	12.66226857	60.33198553	22.3238987	2.936795063	1.127899553
NYNJB NORTH	7.90559055	6.193677788	18.66860646	47.97593152	16.184073	1.786773638	1.285347044
NYNJB SOUTH	1.05298674	2.314040292	12.1775316	60.4673068	19.96597827	2.553035948	1.469120355
SNE	17.5068317	4.751867638	29.65930182	34.27593475	4.390930881	1.050167411	8.364965818
VW	3.89315146	2.500710429	42.14265416	42.114237	1.023017903	0	8.326229042

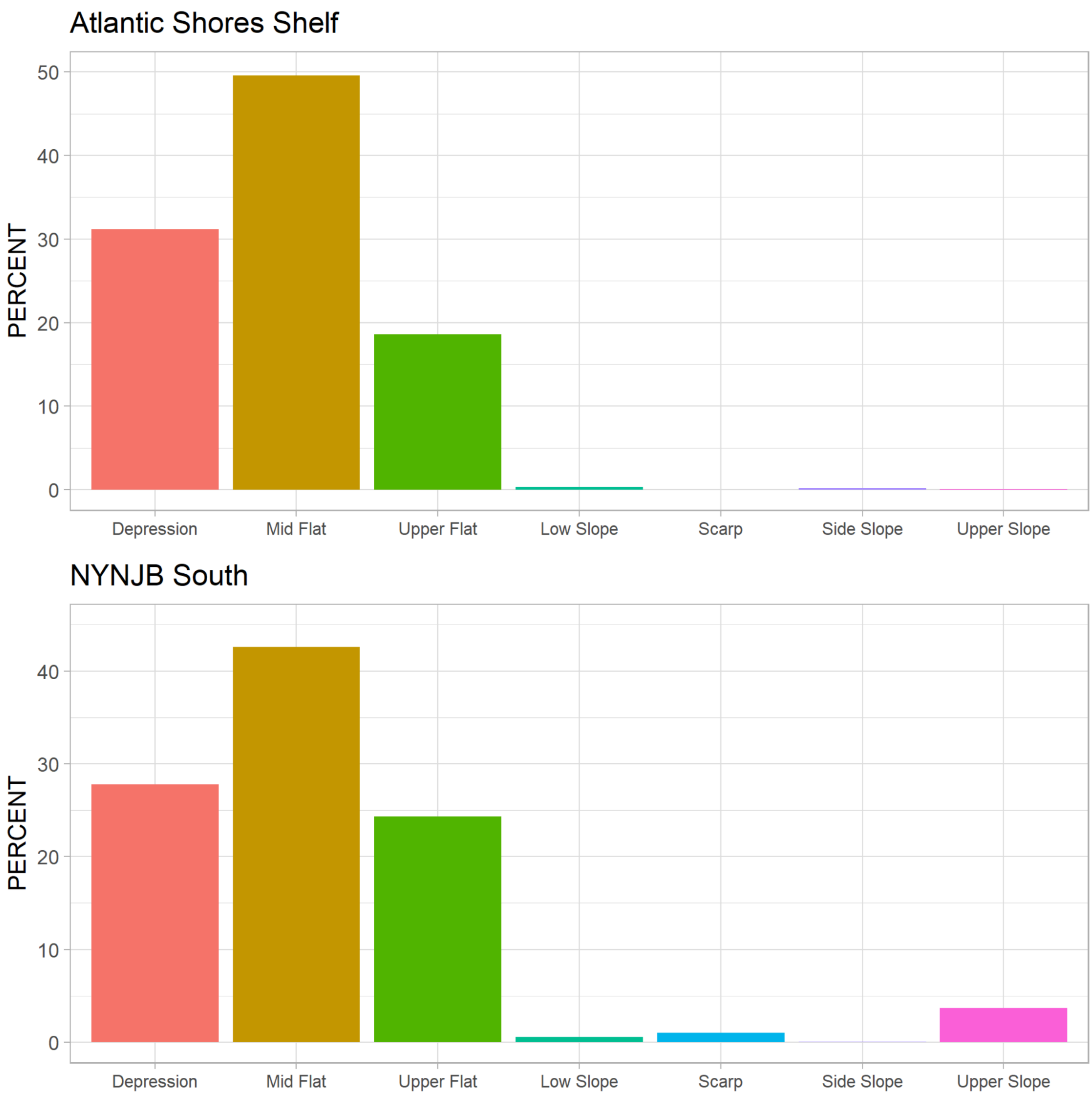
A.5 Seabed Form Relative Percent Coverage for All 21 Wind Farm Sites and 3 Subregions

ZONE-CODE	Depression	Mid Flat	Upper Flat	Low Slope	Scarp	Side Slope	Upper Slope
OCS0486	37.14492873	40.240554	22.0786968	0.382068001	0	0.027768065	0.125984738
OCS0487	30.04989874	54.489321	14.9920663	0.449923795	0	0.012526881	0.00626344
OCS0498	32.51388149	45.858371	21.025329	0.255571613	0	0.22894957	0.117897619
OCS0499	31.20808593	49.607681	18.612248	0.317698225	0	0.196639829	0.057646855
OCS0500	24.49715956	70.898398	4.60444288	0	0	0	0
OCS0501	30.44879465	69.268814	0.28239123	0	0	0	0
OCS0512	14.242147	81.768114	3.98973862	0	0	0	0
OCS0517	27.93713513	42.938843	28.3753472	0.730848646	0	0	0.017825577
OCS0520	17.83973279	81.422524	0.73774274	0	0	0	0
OCS0521	10.40521351	87.964804	1.62998276	0	0	0	0
OCS0522	7.707744047	87.63292	4.57362113	0	0	0.004537823	0.081176607
OCS0532	34.36876902	46.402036	18.7642985	0.170007346	0	0.179452199	0.115437087
OCS0534	26.04794169	73.191228	0.76083009	0	0	0	0
OCS0537	15.46287971	73.879398	10.6577218	0	0	0	0
OCS0538	21.71957341	53.045092	24.9982619	0.189101628	0	0.033370876	0.014599758
OCS0539	29.10926485	45.991803	24.4879776	0.12250671	0	0.070162934	0.218284683
OCS0541	34.85126874	39.182405	25.8556743	0.037567023	0	0.04234828	0.030736655
OCS0542	35.40298308	39.540499	24.867233	0.048826165	0	0.036117985	0.104340847
OCS0544	10.29217266	89.551521	0.15630636	0	0	0	0
OCS0549	34.28006158	60.545306	5.134342	0.023452722	0	0.012628389	0.004209463
OCS0561	16.17106021	82.85239	0.97655	0	0	0	0

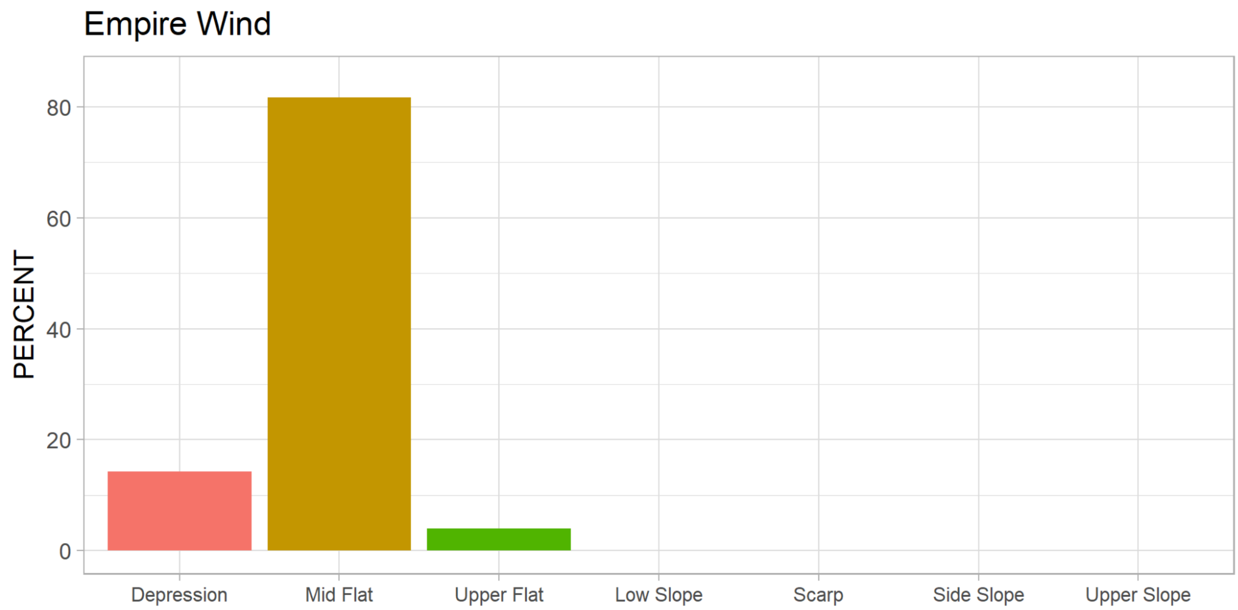
A.6 Sediment Types by Grain Size (in mm) Relative Percent Coverage for All 21 Wind Farm Sites and 3 Subregions

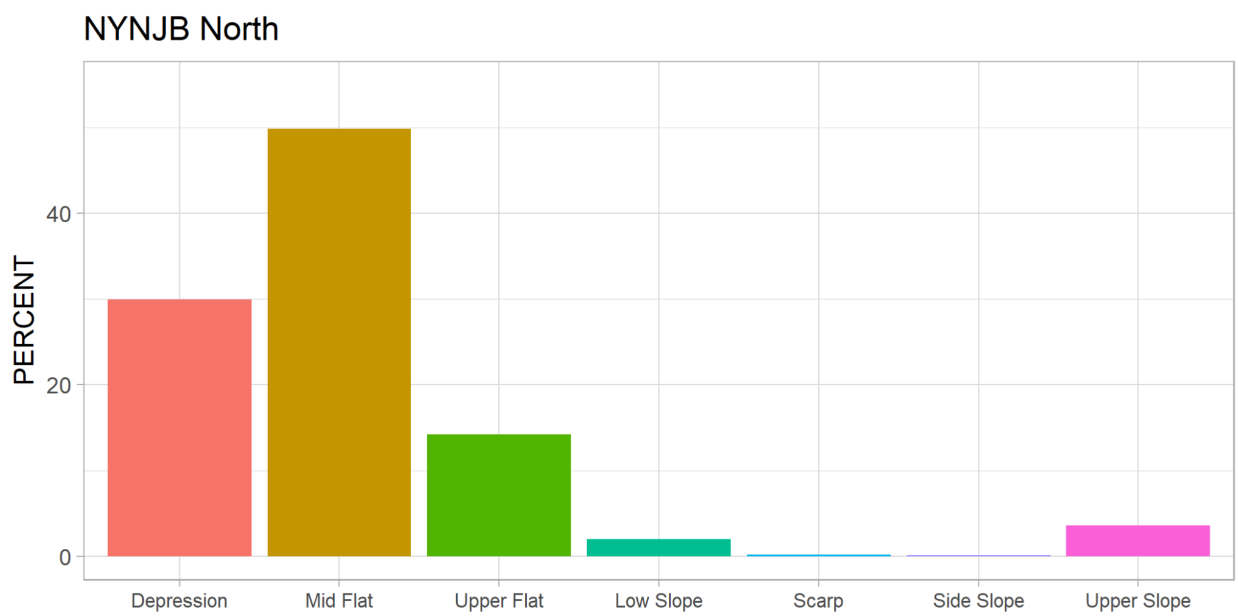
ZONE-CODE	Silt	Very Fine Sand	Fine Sand	Medium Sand	Coarse Sand	Very Coarse Sand	Gravel/Granule
OCS0486	3.4779425	2.709134175	22.0025627	30.67911404	17.42632253	4.740984807	18.96393923
OCS0487	2.5650558	1.988847584	28.2156134	29.46096654	14.55390335	1.765799257	21.44981413
OCS0498	0	0.786334056	13.340564	71.63774403	13.96420824	0.271149675	0
OCS0499	0	0.524156791	5.74293528	62.60255242	31.13035552	0	0
OCS0500	7.3957738	3.826384923	45.9308966	31.01085094	1.541976014	0.028555111	10.26556254
OCS0501	3.8931515	2.500710429	42.1426542	42.114237	1.023017903	0	8.326229042
OCS0512	0	0.617152586	12.6622686	60.33198553	22.3238987	2.936795063	1.127899553
OCS0517	0	0	10.5402542	32.20338983	38.55932203	2.383474576	16.31355932
OCS0520	20.292962	10.09289032	39.2282958	30.38585209	0	0	0
OCS0521	31.287236	9.98375158	39.8447373	18.88427514	0	0	0
OCS0522	21.426006	1.688218391	50.1616379	22.79094828	0	0	3.933189655
OCS0532	0	1.327350907	15.3673584	63.99326977	16.63862404	1.439521406	1.233875491
OCS0534	6.6191219	5.460218409	43.7931803	40.78448852	0.490305326	0	2.852685536
OCS0537	0	0	0	41.46809093	57.27198028	1.259928787	0
OCS0538	0.123793	1.411240406	3.46620451	23.69398366	53.99851448	14.03812825	3.268135677
OCS0539	0	0	2.56104824	60.17470717	26.16636887	11.09787572	0
OCS0541	0	0	2.55412308	82.55898808	14.42471418	0.462174653	0
OCS0542	0	0	3.69311413	86.06147248	10.24541339	0	0
OCS0544	0	0	4.08432148	63.37285903	31.91699605	0.625823452	0
OCS0549	0.0641574	0.149700599	3.78528657	47.88280582	41.42429427	3.058169376	3.635585971
OCS0561	7.3156846	10.50384287	60.9450612	21.23541133	0	0	0

A.7 Seabed Form Bar Graph Showing the Relative Percent Coverage for Atlantic Shores South and NY/NJ Bight South

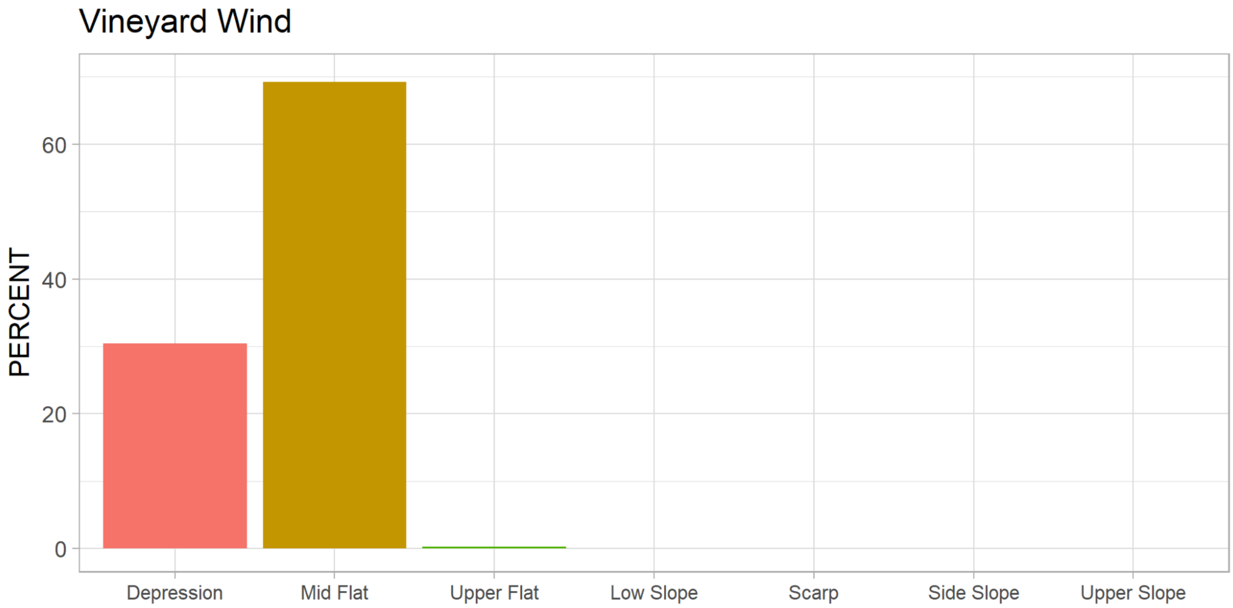


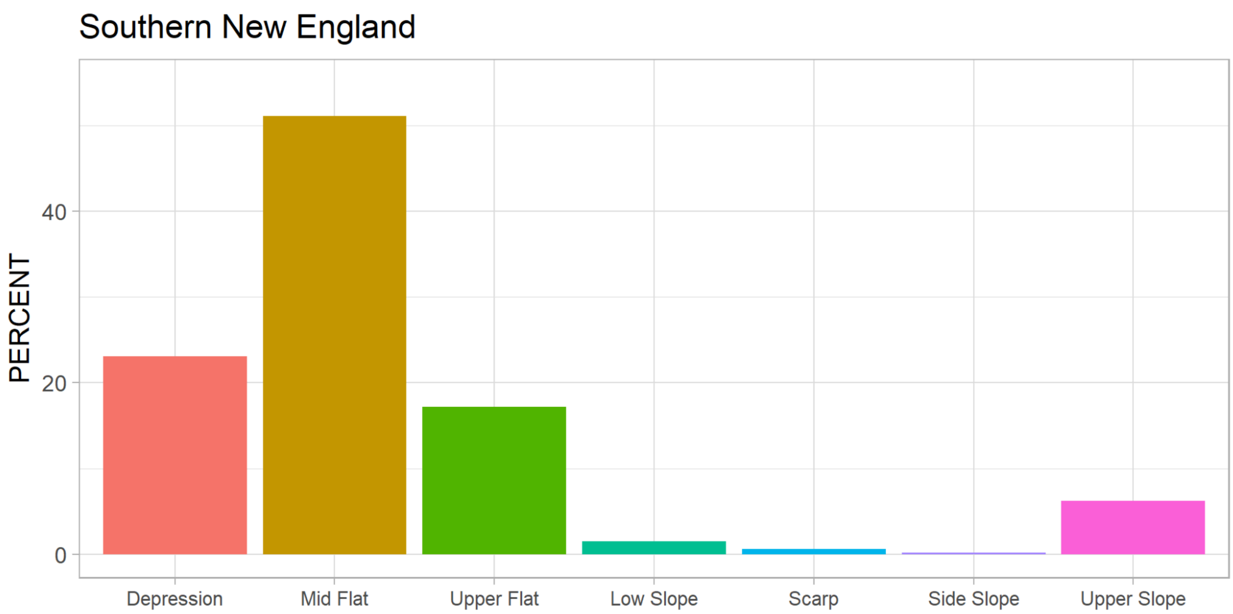
A.8 Seabed Form Bar Graph Showing the Relative Percent Coverage for Empire Wind and NY/NJ Bight North



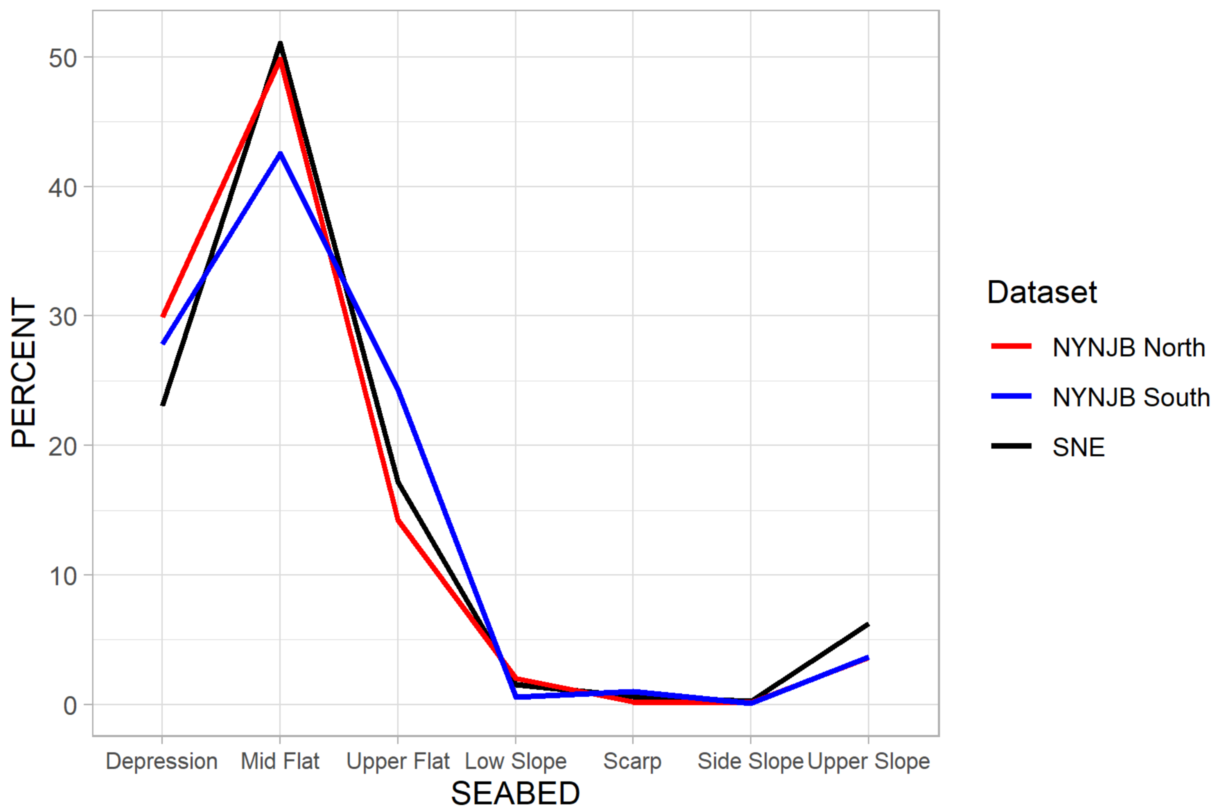


A.9 Seabed Form Bar Graph Showing the Relative Percent Coverage for Vineyard Wind 1 and Southern New England

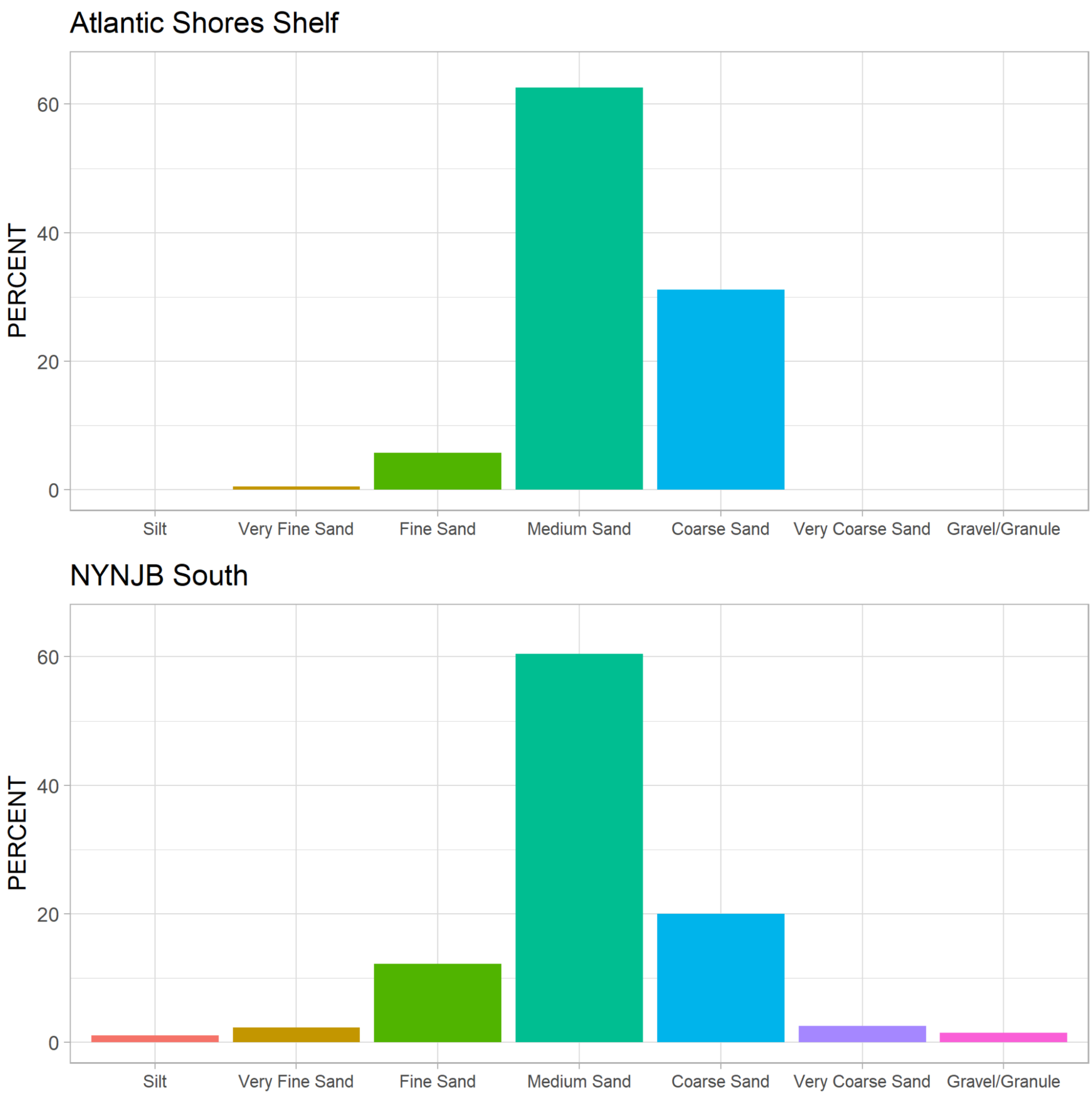




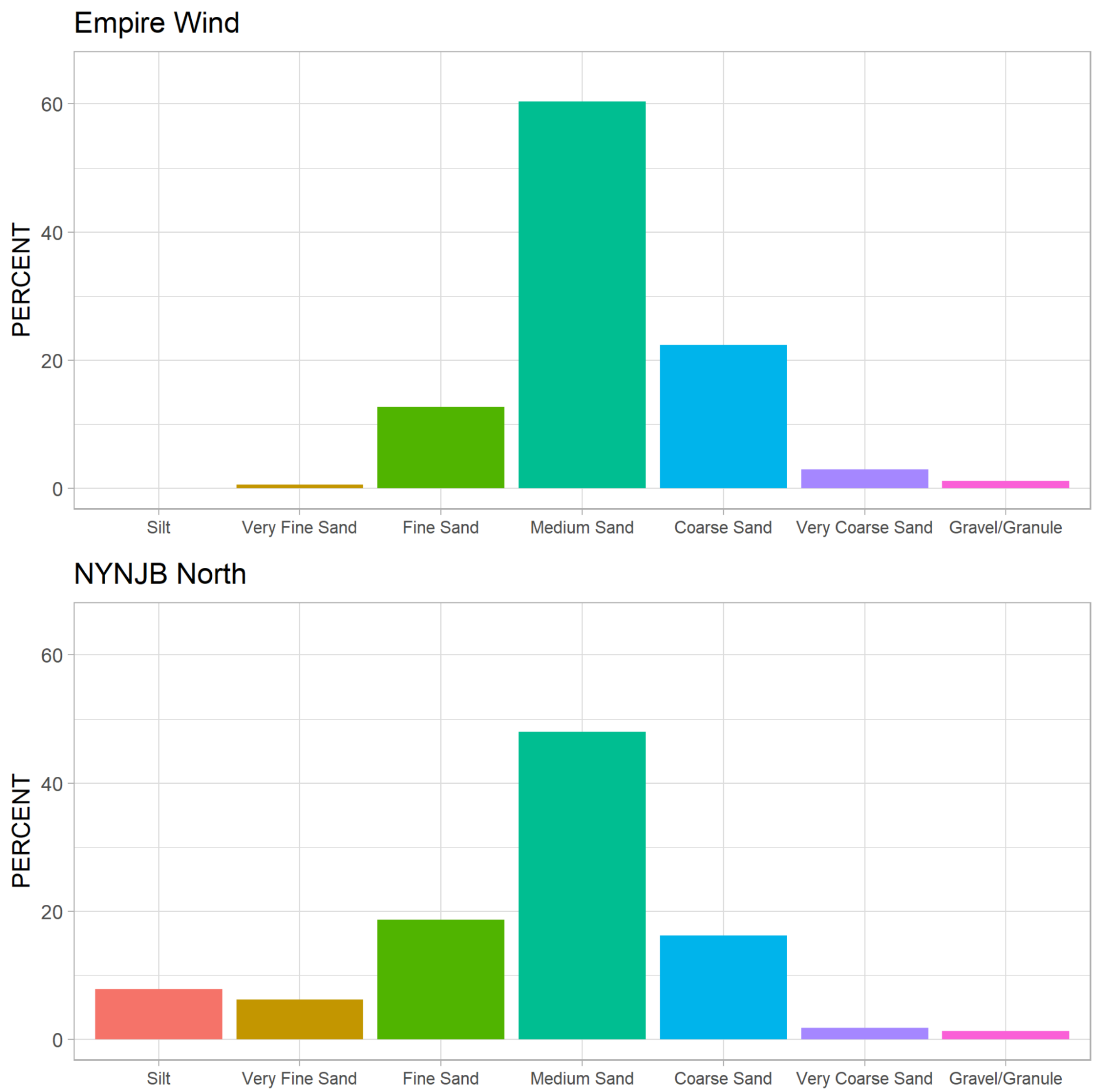
A.10 Line Plot Comparing the Seabed Form Relative Percent Coverage for Southern New England, NY/NJ Bight North, and NY/NJ Bight South



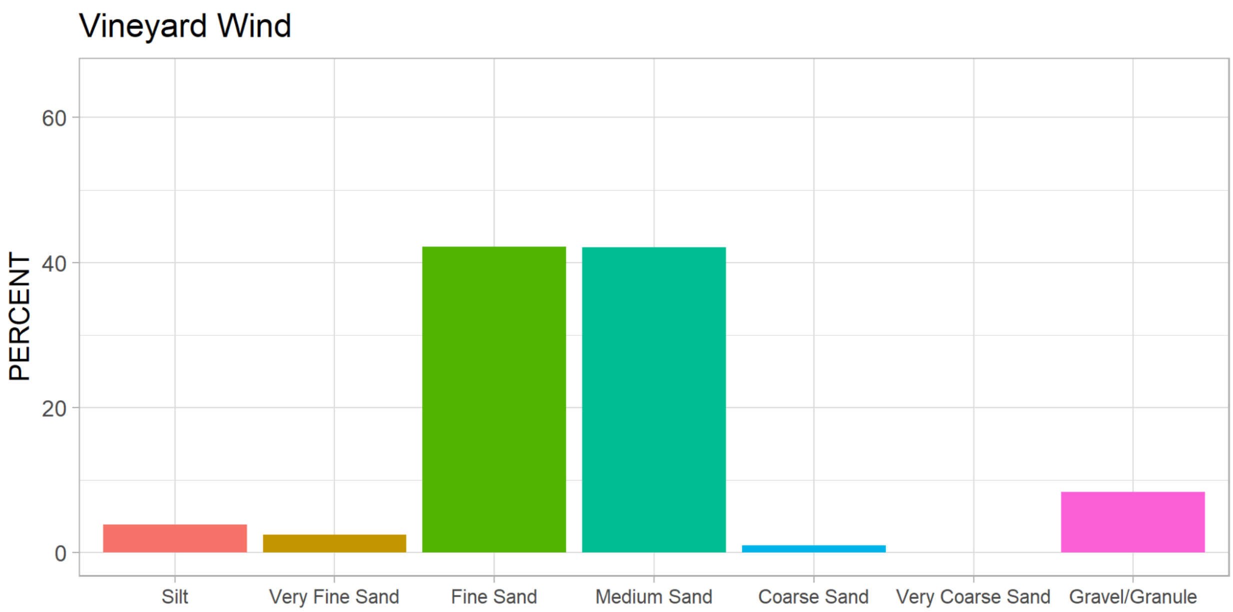
A.11 Sediment Types by Grain Size (in mm) Bar Graph Showing the Relative Percent Coverage for Atlantic Shores South and NY/NJ Bight South

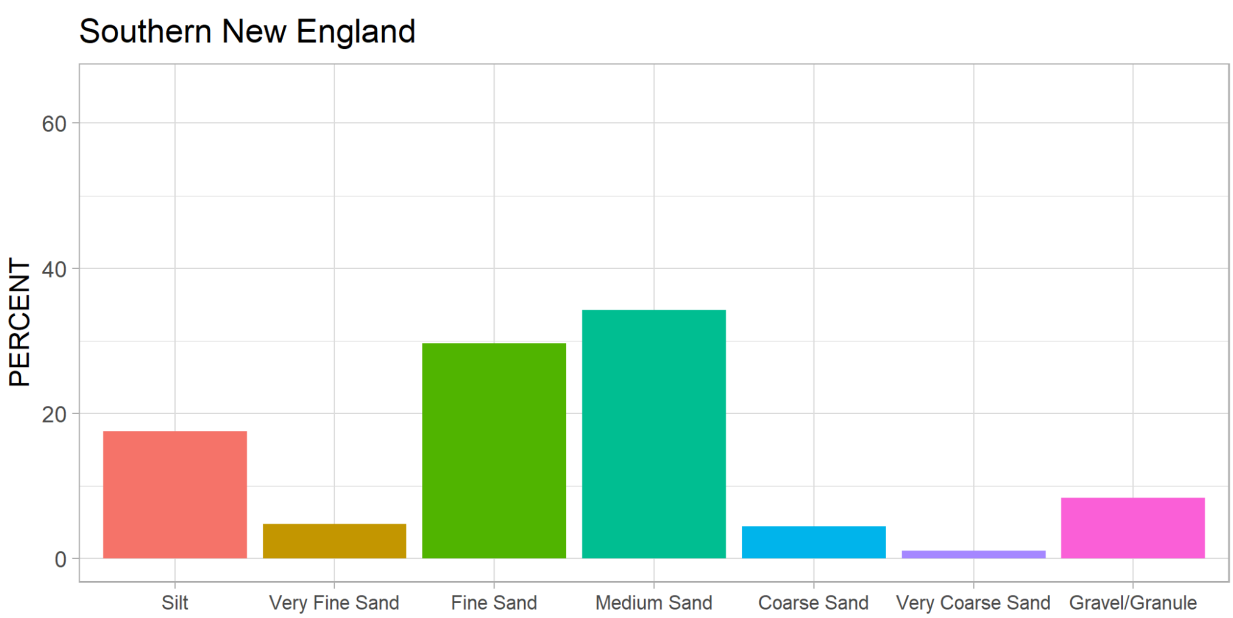


A.12 Sediment Types by Grain Size (in mm) Bar Graph Showing the Relative Percent Coverage for Empire Wind and NY/NJ Bight North



A.13 Sediment Types by Grain Size (in mm) Bar Graph Showing the Relative Percent Coverage for Vineyard Wind 1 and Southern New England





A.14 Line Plot Comparing the Sediment Types by Grain Size (in mm) Relative Percent Coverage for Southern New England, NY/NJ Bight North, and NY/NJ Bight South