23.

Ecological and Service Valuation, a Principal Component and Cluster Analysis Approach:

An Ecological and Service Typology in the Ocean SAMP Area

by

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Executive Summary

Assessing the impact of human activities on coastal and offshore environments is an integral part of planning significant developments in these areas, such as the installation of an offshore wind farm. When human impacts are predictable, as in the installation of coastal or offshore structures, the ecological information is essential to managing these environments. Marine Management Tools (MMTs) integrate biological, and other information such as services, typically in the form of synthetic maps. Such MMTs are useful not only for performing environmental impact studies, but also for managing marine sanctuaries and other protected areas. MMTs are emerging from a recent new conceptual approach, the Ecosystem-Based Management approach (EBM), an integrated approach to management that considers the entire ecosystem including humans and seeks an optimal balance between ecology and society. Optimal balance refers to an ecosystem in healthy, productive, and resilient conditions, which can provide the services humans want and need. (Load and Leslie, 2009). These services are defined as: (i) provisioning services (food, fuel, medicines); (ii) regulating services (biological regulation, climate regulation, human disease control, waste processing, flood protection, erosion control); (iii) cultural services (aesthetics, education and research); and (iv) supporting services (biochemical processes, nutrient cycling) (Load and Leslie, 2009).

There is no standard methodology to assess the state of an ecosystem in this extended sense, including humans, although many methods have been proposed. We prepared a literature review of methodologies used in EBM to assess the health of an ecosystem. It will be subsequently included in an appendix, to complement the literature review provided in the companion report of this SAMP sub-project (French et al., 2010).

In the present study, a Principal Component (PCA) and Cluster analysis (CA) approach is selected to extract homogeneous ecological and socio-ecological sub-regions in the SAMP study area. The PCA-CA is a non-value objective way of mapping the attribute data describing an ecosystem. The PCA extracts the natural variance of the primitive variables describing the area, without assigning *a priori* values, scores, or weights. This results in a quantitative ordination or organization of the data in terms of principal components, ultimately leading to a clustering or a grouping of similar areas into homogeneous zones (CA). The resulting map of clustered zones is more an objective typology than a valuation map. Each newly defined zone is described in terms of ecological or socio-ecological assemblages and biodiversity. Once the sub-regions are

objectively delimited this way, these can be interpreted in terms of values relative to the services, as defined above.

The PCA-CA method is applied to seasonal data (Fall) using a first group of variables corresponding to a biodiversity level 1, defined as the minimal level of acceptable ecological diversity in input, including 12 fishes species, whales and dolphins, and to a second group of variables corresponding to a socio-bio diversity level 1, including 14 ecological variables and 2 fisheries and service variables (mobile and fix gear use and recreational use). The application of the method leads to a partitioning of the SAMP area into ecological and socio-ecological sub-regions. In parallel the method is applied to geophysical variables to help with the cluster interpretation in terms of geophysical variables.

Results, presented in terms of ecological groups and biodiversity index, consistently reflect an onshore-offshore gradient and the geological and sedimentological variance. A deeper water group is isolated from a shallow water group. The intermediate and shallow waters are separated into two groups, reflecting both the oceanographic dichotomy between Rhode Island and Block Island Sound, and variance in geological deposits.

Although still at a stage of development, this marine management tool is proving promising for identifying sub-regions. Major expected future developments are:

- Adding ecological and services variables to more accurately represent the ecological and social environment, and therefore better discriminate the space.
- Developing the cluster valuation method:
    - The biodiversity and services indices are a first attempt at valuation and follow up work should include using and comparing the various standard, or newly developed, indices by Shannon (1947) or others (Derous, 2007; Borja et al., 2007; Spellerberg and Fedor, 2003).
    - The concept of valuation should relate the valuation criteria to the different organizational levels of biodiversity, such as: population, community, ecosystem, which means discriminating between migratory species passing though the area and species living in symbiosis with others, or species associated with a particular geomorphologic feature, or related to a particular oceanographic process, such as upwelling (Derous, 2007).
    - The Concept of rarity must be introduced.

- Assessing the uncertainty of the groups isolated by the clusters, due to uncertainty in the data, and discussing the cluster borders in those terms (i.e., rigid or fuzzy borders).

- Addressing the dynamic aspect of the sub-regions, by introducing time series of the variables rather than mean values in input.

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1 Introduction

Assessing the impact of human activities on coastal and offshore environments is an integral part of planning significant developments in these areas, such as the installation of an offshore wind farm. When human impacts are predictable, as in the installation of coastal or offshore structures, the ecological information is essential to managing these environments. Marine Management Tools (MMTs) integrate biological and other information, such as services, typically in the form of synthetic maps. Such MMTs are useful not only for performing environmental impact studies, but also for managing marine sanctuaries and other protected areas. MMTs are emerging from a recent new conceptual approach, the Ecosystem-Based Management approach (EBM), which is an integrated approach to management that considers the entire ecosystem including humans. The EBM's goal is to manage the ecosystem through explicitly integrating the dynamics between ecological and social domains. This approach is relatively new in the sense that the environment—in this specific case the ocean—is no longer considered as this "sacred untouchable place", or this "free open space", which can be used and abused. The interaction between ecological and social domains, inherent to any society, is acknowledged in EBMs and, therefore, an optimal balance is finally sought, which refers to an ecosystem in healthy, productive and resilient conditions, that can provides the services humans want and need (Load and Leslie, 2009; Arkema et al. 2006; Goldman et al. 2008; Lester et al. 2010). Among many published lists of services, we adopted Load and Leslie's definition, whose relevance depends on the specific ecosystem, which includes: (i) provisioning services (food, fuel, medicines); (ii) regulating services (biological regulation, climate regulation, human disease control, waste processing, flood protection, erosion control), (iii) cultural services (aesthetics, education and research); and (iv) supporting services (biochemical processes, nutrient cycling) (Load and Leslie, 2009)

Although there is no standard methodology to assess the state of an ecosystem in this extended sense, including humans, many methods have been proposed. The concept of nature‘s valuation has been raised, debated, accepted, or refused. It seems that a fundamental step in the concept of nature valuation is the Lauderdale paradigm (1819), which defines public and private wealth and riches as "everything in the world, which is delightful to people, with the additional factor for private riches that it occurs in a certain degree of scarcity". The paradox is that when public wealth becomes relatively scarce, it gains value, but paradoxically falls in the domain of private riches and thus the public wealth decreases (Daly,2007). The ecological valuation process is entangled in this paradox. It seems that, conceptually, one cannot escape “pricing nature “ (Hanley and Barbier, 2009; Wainger and Boyd, 2009; McLeod and Leslie, 2009). There are many methodologies towards this valuation, using or not monetary units, which are more or less complex and more or less complete, but still all of these methods have a common drawback: subjectivity, to a minimal or larger degree, which is inherent to the concept of valuation. A literature review of methodologies used in EBM to assess the health of an ecosystem was prepared and will be subsequently added in an appendix, as a complement to the literature review covered in the companion report of this SAMP sub-project (French et al., 2010).

In the present study a Principal Component (PCA) and Cluster analysis (CA) approach was selected to identify homogeneous ocean areas or sub-regions within the SAMP study area. This method is a non-value and objective way of mapping the attribute data describing an ecosystem (Zuur et al., 2007). The PCA extracts the natural variance of the original variables, which describes the area, without assigning *a priori* values, scores, or weights. This results in a quantitative ordination, or organization of the data (i.e., the principal components), ultimately leading to a clustering or grouping of similar areas into homogeneous zones (i.e., the clusters). The resulting map of clustered zones is more an objective typology than a valuation map. Each newly defined zone is described in terms of original variables and biodiversity (schematic example: deep water, mammals passing through; shallow water, rocky habitat, high biodiversity, bird foraging area). This approach is commonly used in regional geography (Cablk, White, and Kiester, 2002), but less often applied to ocean management, although Jordaan (2010) recently applied a PCA to the Gulf of Main, to extract and interpret the natural geographical structure of the coastal and offshore marine biodiversity. Similarly, Borja et al. (2007) developed a Marine Biotic Index based on a multivariate approach (M-AMBI), to assess the ecological integrity of coastal and estuarine waters, in order to respond to the request of the European Water Framework directive (2000/60/EC). Once the sub-regions are objectively delimited, these can be interpreted in terms of value relative to the service list, as defined above.

It should be pointed out, before we detail our analyses, that the original goal of this study had to be slightly restated, in view of the unavailability of some data and the tight time frame left for the analysis. Specifically, as of July 1st, we were still expecting additional data, but then decided to complete the analysis without it to met the deadline. The present analysis integrates fish data (Collie, 2010) , mammal data (Kinney, 2010), geophysiscal data (Codega and Ullman, 2010), and binary (i.e., use=1; not use=0) fisheries data (Beutel, 2009), representing the services data.

The bird data available at this time was still spatially too sporadic to reliably be included in this analysis. The bird aerial survey currently performed will lead to a denser spatial coverage and will likely be available at the end of the year 2010 (Winarski,2009; Patton,2010). Also, we unfortunately could not have access to benthos data, which should contain the best tracer of ecological health, and the quantitative fisheries data were neither available. In view of additional restrictions on summer and winter fish data, the study will be performed for fall and spring season only . In the current report, only fall season is presented. Spring results will be delivered by the deadline of September 1st.

2 Data source

Data used in the multivariate analysis are grouped into ecological, geophysical, and services variables.

2.1 Ecological data

Seasonal fish biomass by species. Those data were obtained from Jeremy Coolie's team from URI Graduate School of Oceanography (Bohaboy and al., 2010). Data used in the analysis are described in Appendix A of their report. Data are point data in biomass per surface unit (mg/m^2) obtained from 3 sources, Rhode Island Department of Environmental Management (DEM) (monthly,1999 - 2008) , Northeast Area Monitoring and Assessment Program (NEAMAP) (fall 2007, 2008 and spring 2008), National Marine Fisheries Service (NMFS) (spring and fall 1999 – 2008).

Mammals data in sighting-per–unit-effort (SPUE) were obtained from Robert Kenney and Kathleen Vigness-Raposa from URI Graduate School of Oceanography and the Department of Natural resources Science, respectively (Kenney, R.D. and K.J. Vigness-Raposa. 2009).

2.2 Geophysical data

The bathymetry is obtained from NOAA Coastal Relief Model and used to introduce two variables, depth and slope. The depth is the water depth at each grid point (m) and the slope is the maximum slope at each grid cell. It is calculated at each grid cell (200 m by 200 m) as the maximum derivative from the center point of the grid cell to the edge of the grid searching in all direction.

The bottom roughness was provided by John King as the standard deviation of the slope on a radius of 1000 m (J. King, 2010.)

Oceanographic data were obtained from Codega and Ullmann. Variables include in this analysis are sea surface temperature (SST) (deg. C) and stratification (buoyancy frequency squared, 10^{-4} s^{-2}]) (Codega and Ullmann, 2010).

Sediment data includes percentage of clay, silt, sand ,gravel, phi median (Sharma and Baxter, 2010). [The latter parameter is the negative base 2 logarithm of the grain median diameter expressed in mm.]

2.3 Services data

Fisheries data for fixed or mobile gear as well as recreational use data is binary data, reflecting the use or not use of each grid cell (Beutel, 2009). This data is derived from interviews conducted with fishermen.

A detailed description of the data sources can be found in our companion report (French et al., 2010).

3 Methodology

Principal component and cluster analyses are applied to sets of variables to derive typologies. Two ecological typologies are established: (i) a purely ecological typology based on fish and mammals data only; and (ii) an ecological and services typology based on ecological and services variables, including the social and economical domain in the analysis through the fisheries data. Both typologies define homogeneous oceanic ecological or socio-ecological sub-regions. A third geophysical typology defines the area in terms of geophysical sub-regions and is performed to give a physical meaning to the ecological typologies.

Each sub-region is defined by an ecological assemblage of species (or ecological and services group) and can be related to a geophysical sub-region. Let us note that we are using the terminology assemblage in its common definition, referring to a simple group of species, reunited by the clustering analysis, but we do not infer at this point a specific group pertaining to a particular habitat. The ecological assemblages are described in terms of “Biodiversity level 1”. We define biodiversity level 1 as the observed diversity in terms of fishes and mammals, as described in the next section. The group of species considered in this study had to be reduced in comparison to the reference list presented in Bohaboy, Malek and Collie’s report (Bohaboy et al., 2010) because of a lack of spatial coverage for many species, and consequently this analysis underestimates fishes that are hard to catch on trawls. A simple ad-hoc biodiversity level 1 index is introduced to describe each sub-region and is presented in the next section. In a subsequent analysis we plan to extend the list of representative individuals in the ecosystem and present a typology of higher levels. For instance, including birds would lead to “Biodiversity level 2”, or benthos data to “biodiversity level 3”. In a next stage of this study (not presented in the current report), the characterization of each cluster will be refined by comparing various biodiversity indices (Derous, 2007).

The typology methodology is a combination of PCA and CA. The PCA reduces the multi-space into a minimum of independent (principal) components and facilitates the grouping performed with a cluster analysis. The resulting clusters regroup similar assemblages into homogeneous sub-regions.

3.1 Theoretical background

Principal component and cluster analysis can be categorized as Exploratory Data Analysis (EDA) methods. EDA is a means to quantify the inherent structure and variable interactions within a data set, rather than forcing the data to fit a pre-defined model. The fundamental philosophy of EDA is to use as much of the data as possible and extract the structure inherent to the data, free of the traditional assumptions of normality and no-spatial autocorrelation, which are usual obstacles to performing spatial analyses with standard statistical methods (Cablk, et al., 2002). Specifically, PCA and CA are known to be very robust in terms of assumption requirement and “work”, even with non-normal distributions and auto-correlated variables, which are inherent to spatial ecological data (Zuur, 2009; Legendre, 1979)

In short, the Principal Component Analysis (PCA) method reduces the multi-space dimension into a minimal number of independent/orthogonal principal components, defined as a linear combination of the original variables. These linear combinations may or may not have physical meaning. The latter does not really matter in our case, since we use the PCA essentially to eliminate the redundancy embedded in the original correlated variables and explains the maximum possible variance with the lesser number of independent variables. This eventually reduces the number of variables or the dimension of the domain, in which we subsequently perform the cluster analysis. Mathematically, the PCA solves an eigenvalue problem on the basis of the covariance matrix of the original variables, transforming it in a diagonal matrix by applying multiple rotations along the principal directions. The principal components are the "rotated" variables along the principal axes and are independent since they are uncorrelated. Ranking these by decreasing variance, the first principal axis passes through the longest dimension of the "ellipsoid" of the covariance matrix. The next principal axis passes through the next longest directions, respecting the constraint of orthogonality, and so forth for subsequent axes.

The PCA first calculates the dispersion matrix **S**, representing the covariance matrix of all the pairs of N variables y_i ($i = 1, N$), with each other; the matrix is symmetric and the diagonal elements are the variance statistical estimates s_i^2:

$$s_i^2 = \frac{1}{v}\sum_{j=1}^{p}\left(y_{ij} - \bar{y}_i\right)^2 \tag{1}$$

for p objects (grid cell), and the off-diagonal are the covariance estimates:

$$s_{ki} = \frac{1}{v}\sum_{j=1}^{p}\left(y_{kj} - \bar{y}_k\right)\left(y_{ij} - \bar{y}_i\right) \tag{2}$$

with j the index of the object, i and k the indices of the variables, v (usually $p - 1$) the number of degrees of freedom, and the overbar indicating the mean. We find the principal axes of the dispersion matrix by solving:

$$(\mathbf{S} - \lambda\,\mathbf{I})\mathbf{u} = \mathbf{0} \tag{3}$$

with **I** the identity matrix, λ the eigenvalues, and **u** the eigenvectors. The roots of the characteristic equation yield the eigenvalues, which ensure a non-trivial solution to Eq. (3),

$$|\,\mathbf{S} - \lambda\,\mathbf{I}\,| = 0 \tag{4}$$

Substituting these into Eq. (3) allows to calculate the eigenvectors associated with each eigenvalue, which are the principal axes of the dispersion matrix. If the eigenvectors are normalized to have a unit length, one can find the principal components as the coordinates of the original objects in the principal axis. The components of the unit eigenvectors are also the weights of the original variables in the linear combinations, which define the principal components. For instance, the position of a multivariate object j in the first principal axis $k = 1$ is given by the linear combination,

$$f_{1j} = \left(y_{1j} - \bar{y}_1\right)u_{11} + \ldots + \left(y_{jN} - \bar{y}_N\right)u_{1N} \tag{5}$$

of each centered variables y_{ij} describing each object j and their respective weight u_{1i} in the first principal component. The weights of original variables in the principal component allow to gain insight into the physical meaning of each principal component (Jolliffe, 2002).

The Cluster Analysis (CA) calculates the distances between objects in the new multivariate principal components space and regroups similar objects into clusters, based on their proximity in that space. The *k-means* clustering method was selected to perform the partitioning. Each cluster in the partition is defined by its member objects and its centroid. The centroid for each cluster is the point from which the sum of distances from all objects in that cluster is minimum. The method uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. This algorithm moves objects between clusters until the sum cannot be decreased further. The result is a set of clusters that are as compact and well-separated as possible.

3.2 Post clustering data analysis

Physical areas regrouped into a cluster at the end of the PCA-CA analysis, are finally described in terms of the original ecological and services variables characterizing the cluster, as mammals or fish species diversity or abundance; this in turn allows finding an interpretation or meaning for this particular cluster. In order to facilitate this interpretation we developed an ad-hoc biodiversity index combining the relative abundance of a specific species in a cluster, as compared to its general abundance in the entire SAMP area, and the variety or richness of species observed in significant abundance. The abundance is measured in unit of the original variable, e.g., biomass for fishes and view per unit effort for mammals. The relative abundance included in the index is a measure of the mean value of the variable in each cluster, as compared to the general probability distribution of the variable. [Note that these distributions were first normalized for fish biomass, by using the logarithmic transformation of the original variable. Hence, the principal components, which are linear combinations of normal variables, are normal as well. More details are given later on this aspect of data preparation.] In the biodiversity index, if the mean value observed in the cluster pertains to the 1st quartile of the probability distribution, the relative abundance is given a score of 0; if this mean pertains to the 2nd, 3rd, or the 4th quartile the score is 1, 2, or 3, respectively.

Each variable is thus characterized by a standardized score of abundance. The sum of those scores, standardized on a scale of 1 to 10, defines the “Biodiversity index level 1”. The group of variables, which have a score of at least 2 (mean cluster value > 50 % of the general population for this variable) defines a cluster assemblage. We refer to "Biodiversity index level 1" to indicate the level of diversity in species that this index represents. The 14 variables used here are assumed to represent the minimal representative level of diversity. It is hoped that, in the near future, additional data such as birds and benthos will be available, which will allow developing a similar biodiversity index, referred as level 2 and 3. It should be emphasized that we do not propose this index as a new standard of diversity estimation, to replace those already used as standard reference (Shannon, 1947; Derous, 2007; Borja et al., 2008; Spellerberg and Fedor, 2003). Instead, this index should just be viewed as an *ad hoc* local tool, developed to help in identifying the meaning of clusters isolated by the PCA-CA method, considering the specific data used in this analysis. The concept of biodiversity as well as its valuation is discussed in Appendix "More literature and Important definitions" (This appendix will be added by deadline September 1st.)

This biodiversity index is the first step towards valuation. Once the clusters are qualitatively identified, they can be affected a value. In this case the value has only a discriminative role and we do not pretend that it represents an intrinsic value. Future work will focus on valuation, represented here by the biodiversity index, which should be expanded to relate the valuation criteria to the different organizational levels of biodiversity, such as population, community or ecosystem. This will require discriminating migratory species passing through the area from species living in symbiosis with others, or species associated with a particular geomorphologic feature, or related to a particular oceanographic process such as upwelling.

Additionally we introduce a second index, referred to as "services index", complementary to the biodiversity index and based on the same methodology, to assess the relative value in terms of fisheries use of mobile or fixed gears, and recreational variables. This index is used as a proxy for food provision and recreational services, which are combined as a so-called generic "services" index. Goods and Services provided by biodiversity addressed in this study are referred to McLeod and Leslie classification (2007) modified from United Nation Environment Program official classification (2006) (**Table 1**)

Table 1: Goods and Services provided by biodiversity addressed in this study

McLeod and Leslie classification (2007) modified from UNEP 2006	Sub-Categories addressed in this study	Valuation tool introduced in this study
Provisioning services	Food	Service Index
Cultural services	Recreation	
Regulating services		
Supporting services	Life support Biologically mediated habitat	Biodiversity level 1 index

4 Data preparation

In a preliminary step, prior to performing the PCA-CA analysis, outliers are removed from the data set and, optionally, data is normalized for some variables. Figure 1 shows that the log-transformed biomass distributions, for each of 3 survey agencies, closely match a normal distribution.

For outliers, the probability distribution of each variable is first estimated, and outliers are isolated and removed, when observed to be outside the centered 99% confidence interval of the distribution. Such outlier values are set to the extreme value in the confidence interval at 99%. Data is normalized, when appropriate, for some variables, in order to obtain a multivariate distribution as close to multi-normal as possible (although, normality of the variables is not required by the method). The multivariate data is re-interpolated on a standard grid, here 200 by 200 m, using a krigging interpolation scheme. Seasonal typologies are established for Spring and Fall. Winter and Summer are omitted in the present analysis, for lack of a representative spatial distribution for most data.

The analysis is based on the assumption that we have a complete spatial coverage for each variable. Therefore, all fish data from the 3 sources was combined to have the most extensive possible spatial coverage. Differentiating between sources was not possible since the spatial coverage would have been too sporadic and would have affected the validity of the analysis more significantly than the extra-variance introduced, by causing a potential bias in the survey standardization. Erin Bohaboy, Anna Malek, and Jeremy Collie show in their report (Bohaboy et al., 2010) that there is a significant variance due to the survey agency. This variance was investigated, but in view of the very little overlapping in location of the three surveys, it was not possible to accurately estimate the part of the variance truly due to survey bias from that due to the location or depth.

From the biomass distributions regrouped by survey agencies, we see in Figure 2 that all data points belong to the same population since their confidence intervals overlap. This is part of the theoretical justification for aggregating the three sources. However there are obviously slight differences between the three surveys. From Figure 1, we see that the DEM and NEAMAP data are indeed extracted from the same population, but show a slight nearly constant bias. This bias can be a bias in the survey standardization or a true difference due to the catching depth, since DEM surveys are systematically done in very shallow water.

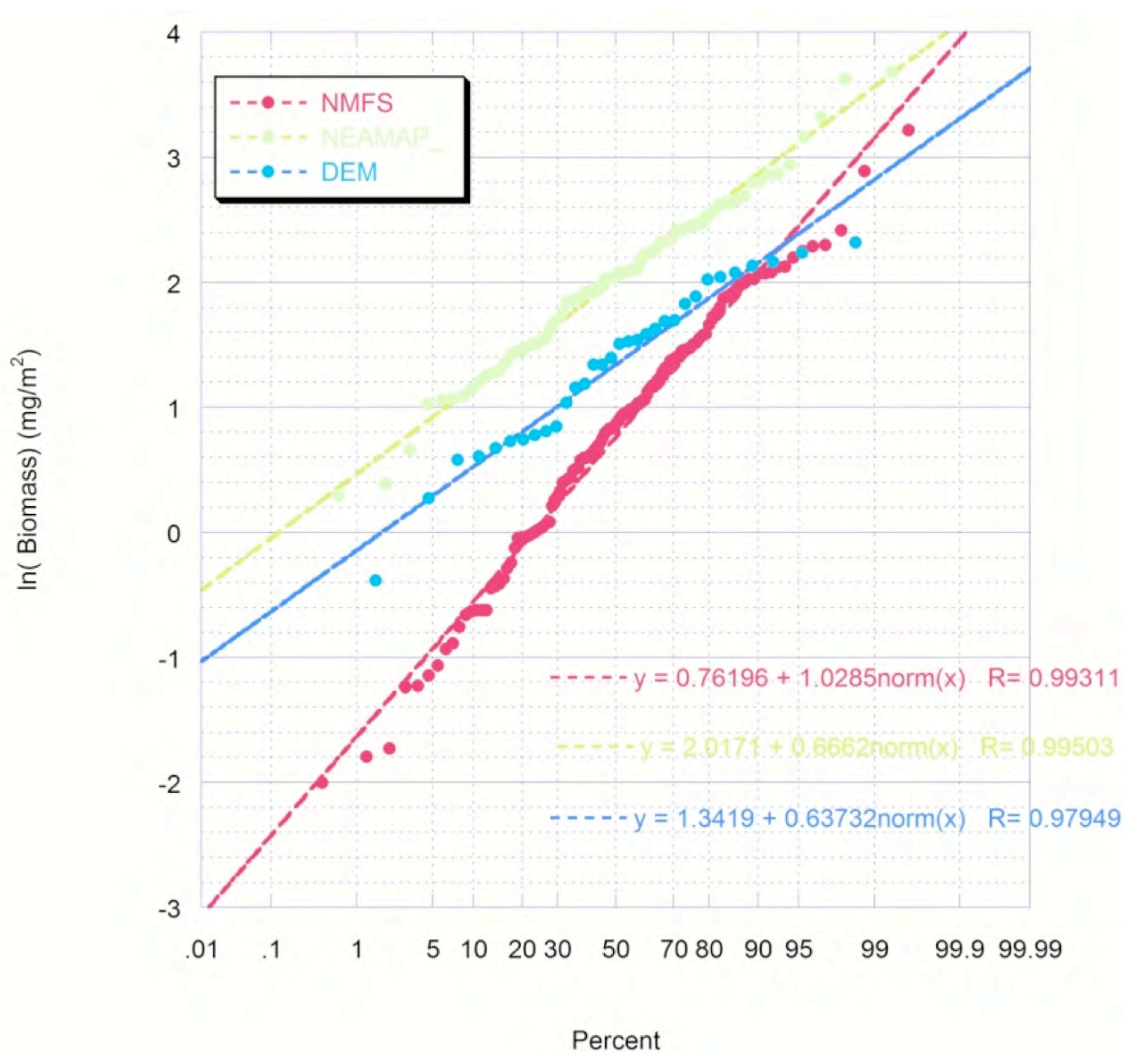


Figure 1:Normality test of the log-transformed Total Biomass [ln(mg/m^2)] for each of the 3 survey

agencies: NEAMAP, DEM, NMFS.

The NMFS population in Figure 1, however, diverges the most from the two others populations, showing a smaller mean value and a larger variance. NMFS survey are the most spread out within the SAMP area, going from shallow onshore waters to deep offshore areas, and therefore are expected to show a larger variance. This divergence could also result from using larger nets (i.e., yielding less small fishes) or different boat speeds in the survey. The sampling period is also significantly different. Those sources of variance could be assessed and accurately addressed, with more overlapping data and a time series analysis. The part of the variance due to the survey bias could be estimated and a corrective term could be applied to standardize the survey. This question could be addressed in an extension of this study, but in the present analysis the aggregation was a necessity, in order to minimize the variance due to under-representation, despite the potential for adding variance due to sampling bias.

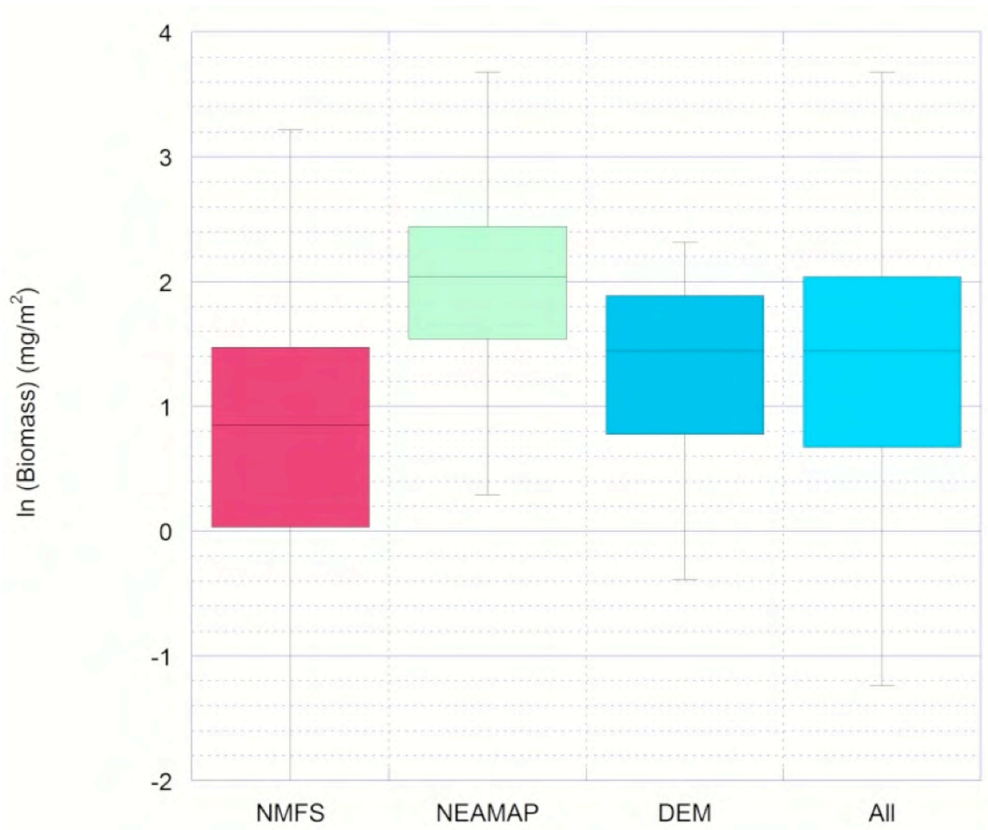


Figure 2: Box plot representation of the samples for the 3 surveys and for all data aggregated together. 25 % to 75% of the population are represented in the boxes. The "error bars" define the confidence intervals at 95 %.

4.1 Ecological data

Fish variables are assumed to be representative if more than 30 surveys are obtained for the area (in statistical analysis, this number is typically the accepted minimum number of individuals in a sample extracted from a normal distribution, for the sample distribution to behave sufficiently normally). For the Fall, 12 species matched this criterion:

American lobster, *Homarus americanus*

Atlantic sea scallop, *Placopectin magellanicus*

Black sea bass, *Centropristis striata*

Bluefish *Pomatomus saltatrix*

Butterfish ,*Peprilus triacanthus*

Little skate, *Leucoraja erinacea*

Longfin squid, *Loligo peali*

Scup, *Stenotomus chrysops*

Silver hake, *Merluccius bilinearis*

Summer flounder, *Paralichthys dentatus*

Winter flounder, *Pseudopleuronectes americanus*

Winter skate, *Leucoraja ocellata*

Fishes' biomasses are log-normal distributed. Data was normalized for each species, using the natural logarithm transform (see Fig. 1).

Mammals data was regrouped into Whales and Dolphins categories, to obtain a significant spatial coverage, making it possible to have the data included in the analysis. For the Fall, Whale and Dolphin categories regroup the following species:

- Whales: North Atlantic Right Whale; Fin Whale; Common Minke Whale

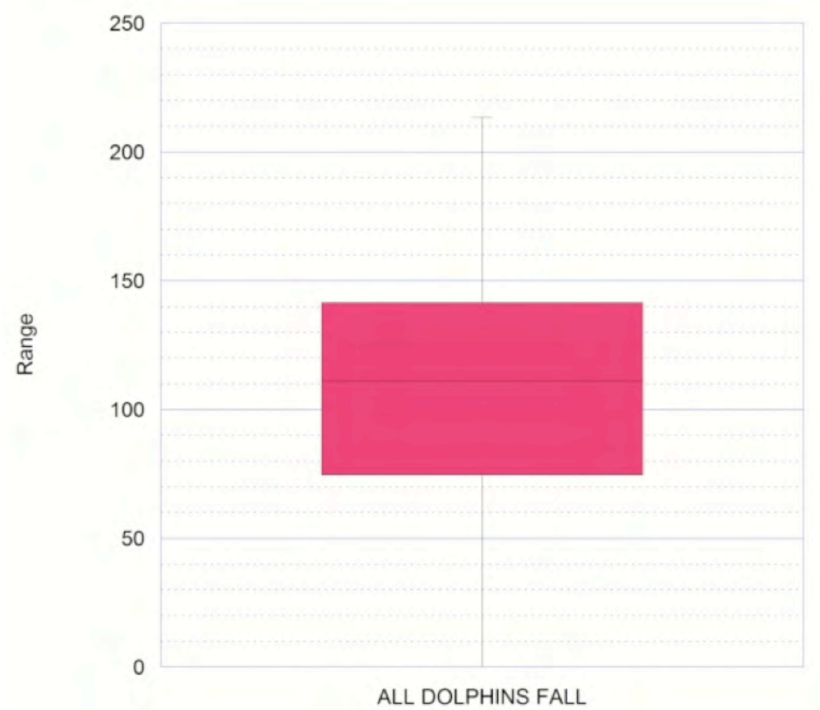


Figure 3: Probability distribution of the entire Fall Dolphin population in the area of occurrence

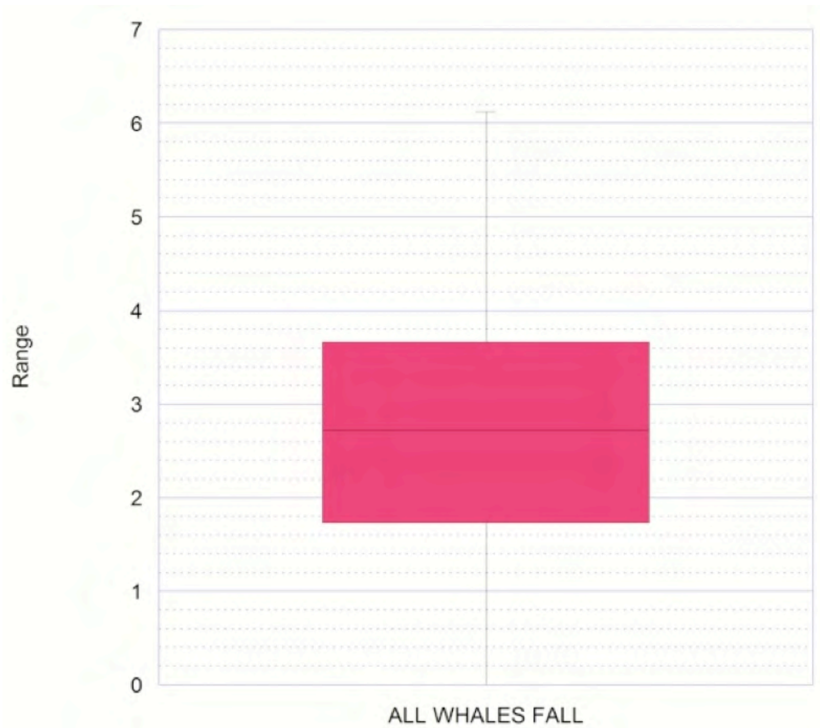


Figure 4: Probability distribution of the entire Fall Whale population in the area of occurrence

- Dolphins:

Short-beaked common dolphin

Atlantic white-sided dolphin

In the area of occurrence it is found that mammals data, grouped into Whales and Dolphins in view per unit effort, is normally distributed.

The mammals mapping (Appendix A) however shows that there are non-occurrence areas, which biases the normal distribution with a tendency to create a bimodal distribution, with a peak at zero (figure in Appendix B).

When applying the spatial interpolation over the 200 by 200 m grid, the typically 30 to 130 ecological data points are re-interpolated to about 130,000 points covering the entire grid. The first step is to check the validity of such a drastic spatial interpolation. To do so, the probability distributions of the observed data points are compared with the probability distributions of the interpolated data points. Results are shown in Appendix B in the form of cumulative probability distributions for each variable. This comparison shows that both probability distributions for each species are in good agreement. The highest discrepancy occurs in extreme lower values, which are over-represented in the interpolation, reflecting either an under-representation of the data in boundary areas, an inhomogeneous data representation in the sampling, or a true discontinuous spatial representation. Discussing those issues could be done in more depth in a follow-up study, but the outcome of this discussion should not significantly affect the current analysis, since those discrepancies only affect the lower tail of the distributions and concern a small percentage of the SAMP area.

4.2 Services data

Each set of data: mobile gear, fixed gear, or recreational, is provided in a binary format (0=no use; 1=use) this format is transformed into a continuous variable between 0 to 3, by creating a fishing index summing the three use at each grid cell and re-interpolating these on the 200 by 200 m grid.

5 Fall Season Ecological Typology

5.1 Principal component and cluster analysis

The principal component analysis is applied to variables defining the biodiversity of the area: 12 fish species and 2 mammals variables (whales and dolphins). The principal component analysis shows that the first principal components expresses about 23 % of the variance of the original variables, but 8 components are required to express 80 % of the variance (Fig. 5). The cluster analysis is performed in the reduced space of 8 principals components, since 80 % of the variance explained is the usual accepted threshold to select the number of principal components kept in such an analysis (Zuur, 2009). Results are presented for a total of 4 and 5 clusters. Comparisons of the scores of each cluster in the first and second principal component domains and the mapping of each cluster (Figs. 6-8) show that the first component represents the onshore/offshore gradient. This result is consistent with Jordan's results in his work in the Gulf of Main. Comparing the clustering for 4 and 5 clusters shows that one additional cluster better differentiates the intermediate depth clusters into 2 sub-areas, relatively separating Block Island sound from Rhode Island sound.

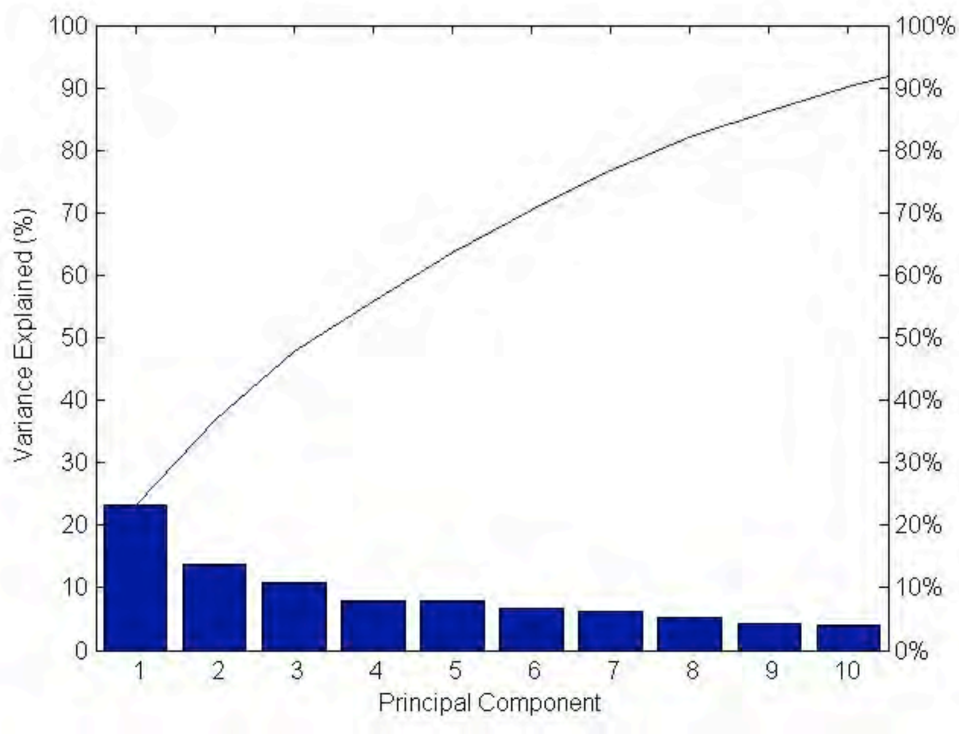


Figure 5:Part of the variance explained by each principal component

It is important to point out that this grouping is based on ecological variables only. No geophysical data are introduced at this stage. Each cluster is defined by a specific ecological assemblage of species used in the analysis. In order to summarize the ecological assemblage of each cluster, as detailed in section 3.2, we developed a simple Biodiversity index combining fish abundance and species diversity. In parallel each cluster is defined with a set of representative geophysical variables. This is discussed in the next section.

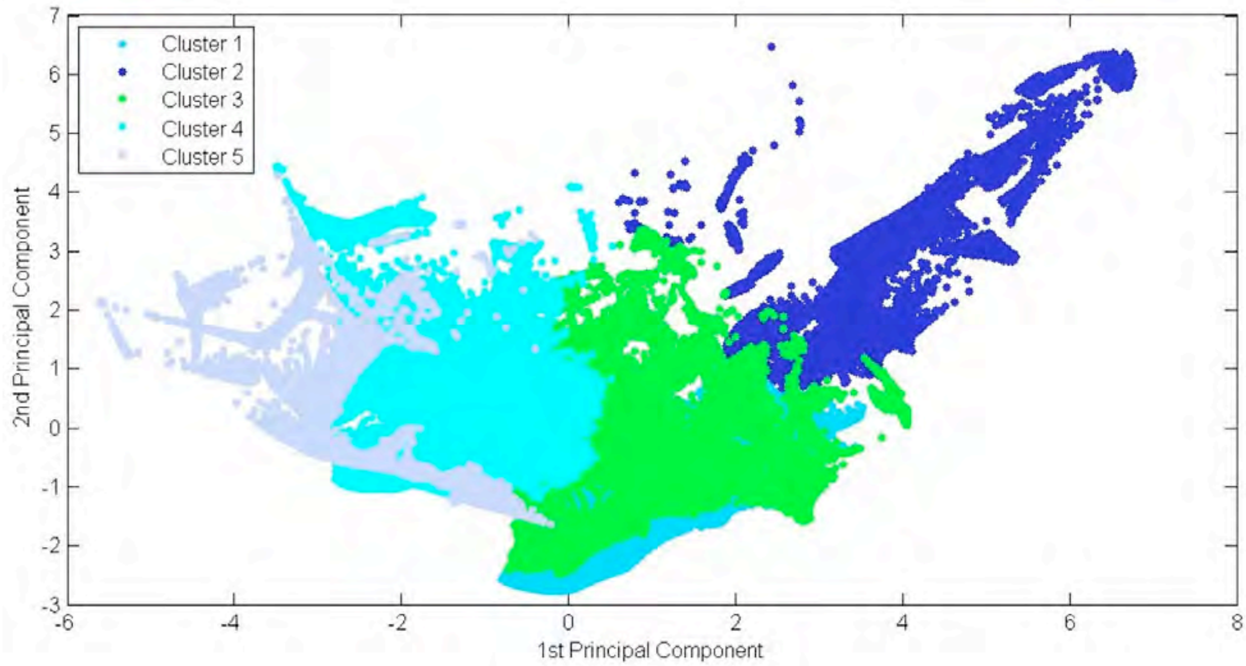


Figure 6 : 5 ecological clusters mapped in the domain of the first and second principal components

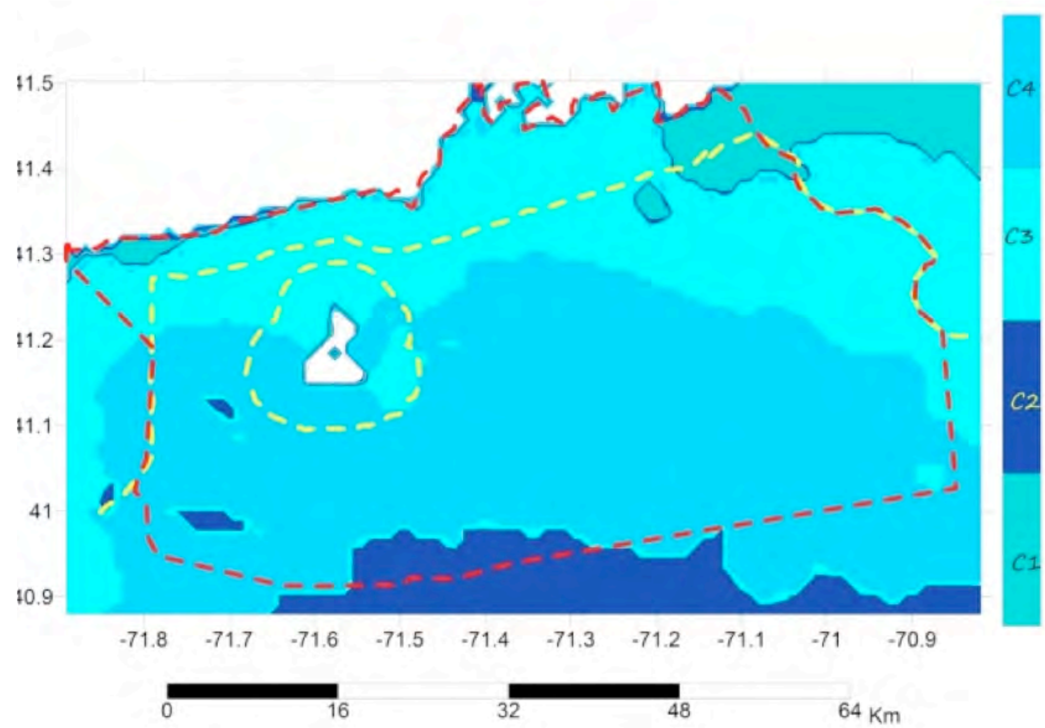


Figure 7 : 4 ecological clusters (biodiversity level 1) mapped in the SAMP area for Fall

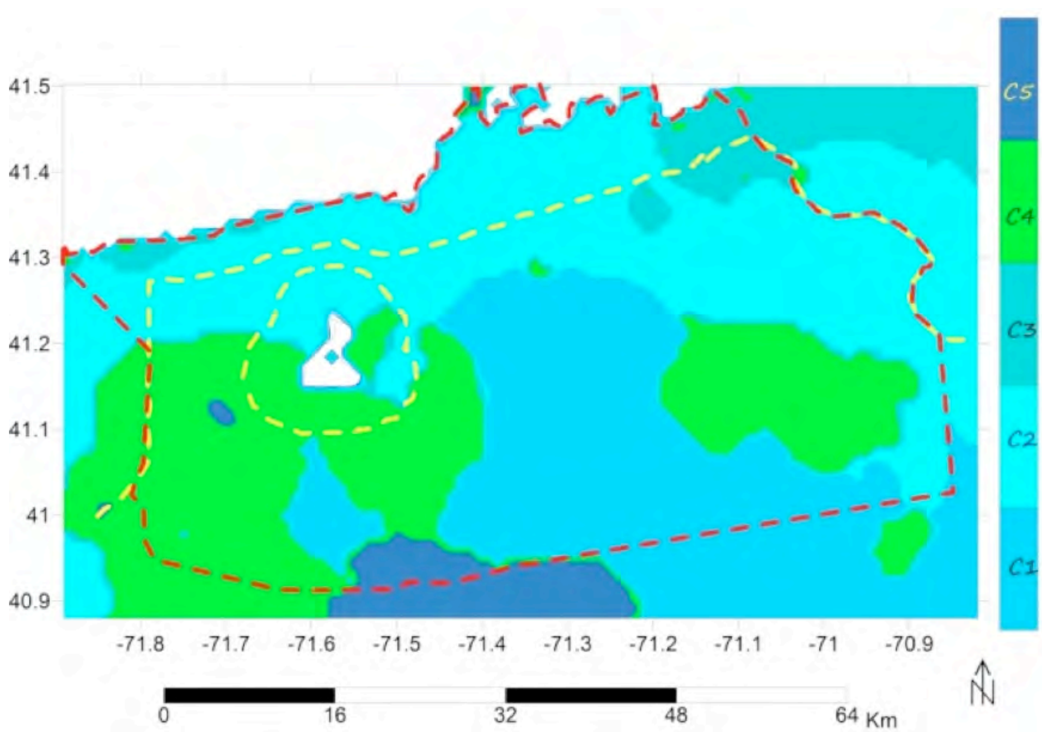


Figure 8 : 5 ecological clusters (biodiversity level 1) mapped in the SAMP area for Fall

Table 2: Ecological Biodiversity --level 1—index for fall season in SAMP area

Ecological Biodiversity Level 1 Index					
Species	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
American Lobster	2	3	0	1	1
Black Sea bass	0	1	2	2	0
Butter fish	0	2	3	0	0
Squid	1	1	3	0	1
Scup	1	2	3	0	0
Summer flounder	1	1	2	2	0
Winter Skate	1	2	2	1	0
Blue fish	2	1	0	2	3
Little Skate	1	2	2	0	0
Scallops	2	1	1	2	2
Silver Hake	3	1	1	1	1
Winter Flounder	2	1	0	1	1
Whale	2	1	1	2	2
Dolphin	2	1	1	1	1
Sum	20	20	21	15	12
Index[1-10]	**9.5**	**9.5**	**10**	**7.1**	**5.7**

5.2 Biodiversity level 1 typology

In order to facilitate the cluster interpretation, scores are calculated based on the relative abundance in each cluster as compared to the general population, as well as a diversity index, combining relative abundance and significant diversity, as defined in section 3.2. The scores and index values are given in

In addition each species considered significant and taken into account in the diversity index (score higher than 1 or mean value larger than 50 % of the global population) is defined as pertaining to the cluster assemblage characterizing the cluster, and is mapped in Figure 9, using various symbols whose size is proportional to this score (score 2 (3rd quartile)=small symbol; score 3 (4th quartile)=large symbol).

The complete score combinations, defining each cluster assemblage, are presented in diagram format in Figure 10.

5.3 Geophysical Interpretation

In order to explore cluster relationships with geophysical conditions, each cluster is related to geophysical variables. These are water depth, bottom slope, bottom roughness, phi median, sea surface temperature (SST) and stratification, which were described in the data section. As for biodiversity, a score is given to each geophysical variable based on comparing its mean value inside the cluster to its probability distribution in the entire SAMP area (Table 2). The method of scaling is identical but the percentile scale is slightly different, giving a score of 4 for above the 95 % percentile (25%, 50%, 75%, 90%, 95%).

Clusters 1 and 5 are both in deep water where the SST is the highest in the Fall as well as the bottom stratification. Cluster 5 is in flat smooth sandy deep water. Cluster 3 is in homogeneous shallow water, with the highest bottom roughness, slope and clayish sediments, coldest SST and no stratification. Clusters 2 and 4 are both in relatively shallow water, although cluster 4 is relatively further away from the main shore, since mostly around Block Island, and are both in relatively steep, rough bottom geology. Cluster 2 is, however, in a well mixed area with very little stratification, as expected from being close to shore areas. Cluster 4 has some stratification, but far less than for the adjacent Cluster 1. Both Clusters 2 and 4 have low SST, as expected from their closeness to shore. Cluster 4 diverges from the adjacent Cluster 1, as well, regarding those variables, definitely marking the difference in the oceanographic climatology of Rhode Island and Block Island Sound.

Using all those tools and comparing the cluster analysis for 4 and 5 clusters, as well as the results of the PCA, it is clear that the primary variable guiding the sub-regionalization is the depth/distance to shore, subdividing primarily the ecological assemblages into coastal and deep water assemblages; the second factor is a parallel to coast discontinuity related to two processes: (i) primarily a discontinuity in the geology and bottom topography, creating shallower waters with rough habitat, such as in the West of Block Island; and (ii) secondarily the oceanographic discontinuity between Block Island Sound and Rhode Island Sound (Codega and Ullmaan, 2010).

Looking more closely at Figs. 9 and 10 and Table 2, we see that the coastal assemblage is correlated with shallower, well-mixed, and colder waters. In those, were found in great quantity the usual shoreline, shallow water species, such as Summer Flounder, Scup, Little Skate, Lobsters Squid. The coastal assemblage in the north-eastern part of the SAMP area is particularly diverse and more defined by rocky species, such as Sea Bass, Scups, Squids. The offshore assemblage is correlated with deeper, stratified, and colder waters, with smooth sandy bottom. It regroups Whales and Dolphins, Scallops and migratory species such as Bluefish. The partitioning of the intermediate area follows relatively closely the bottom roughness and the sedimentology. The rocky rough shallow water area of Block Island sound regroups rocky species, such as Sea Bass; migratory species, such as Bluefish are present too, as well as whales. In the relatively smooth sandy/clayish bottom of Rhode Island sound, the semi-pelagic Silver Hake is highly present as well as the Winter flounder.

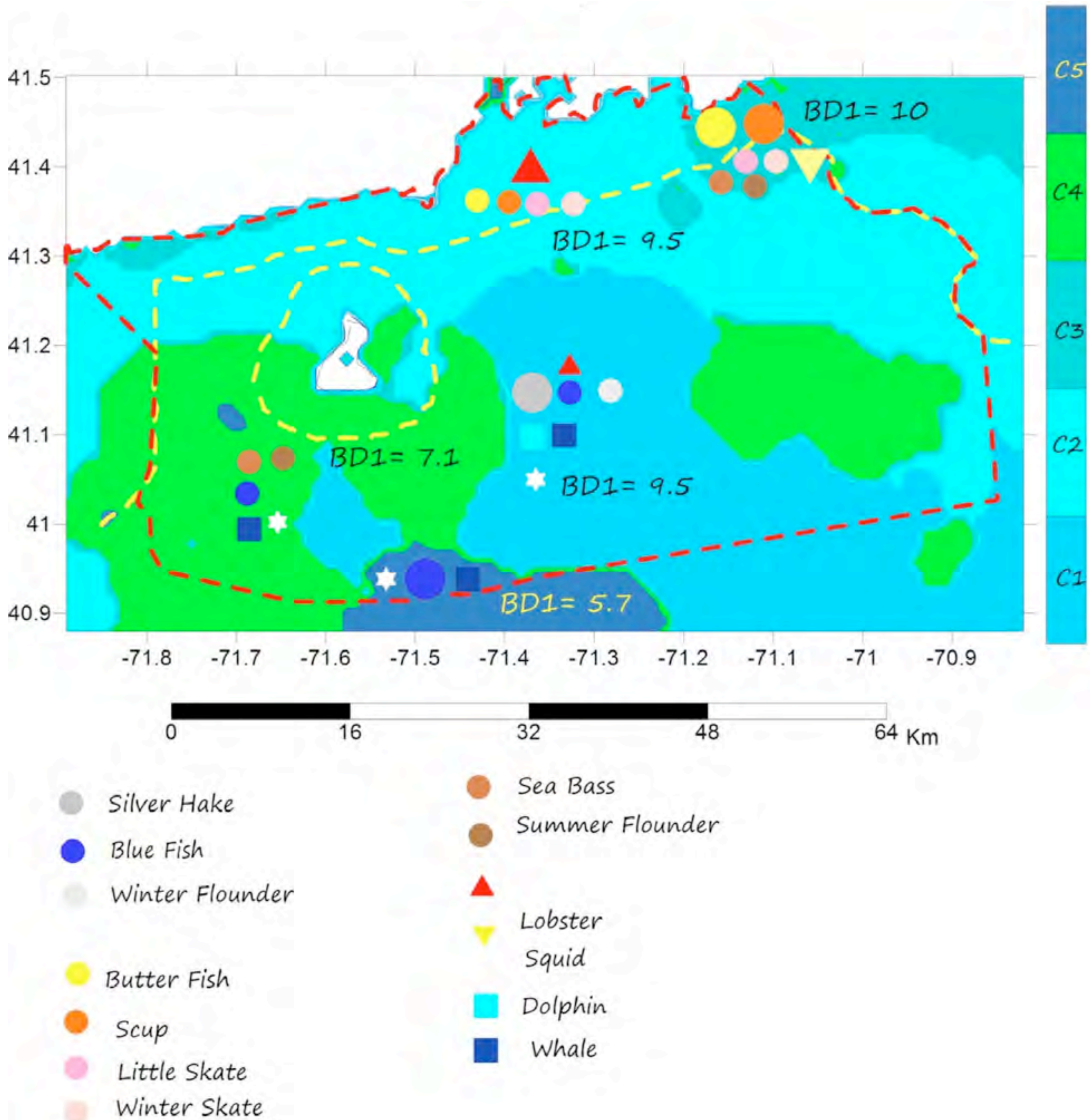


Figure 9: Ecological typology of biodiversity level 1 in SAMP area for Fall based on PCA-CA

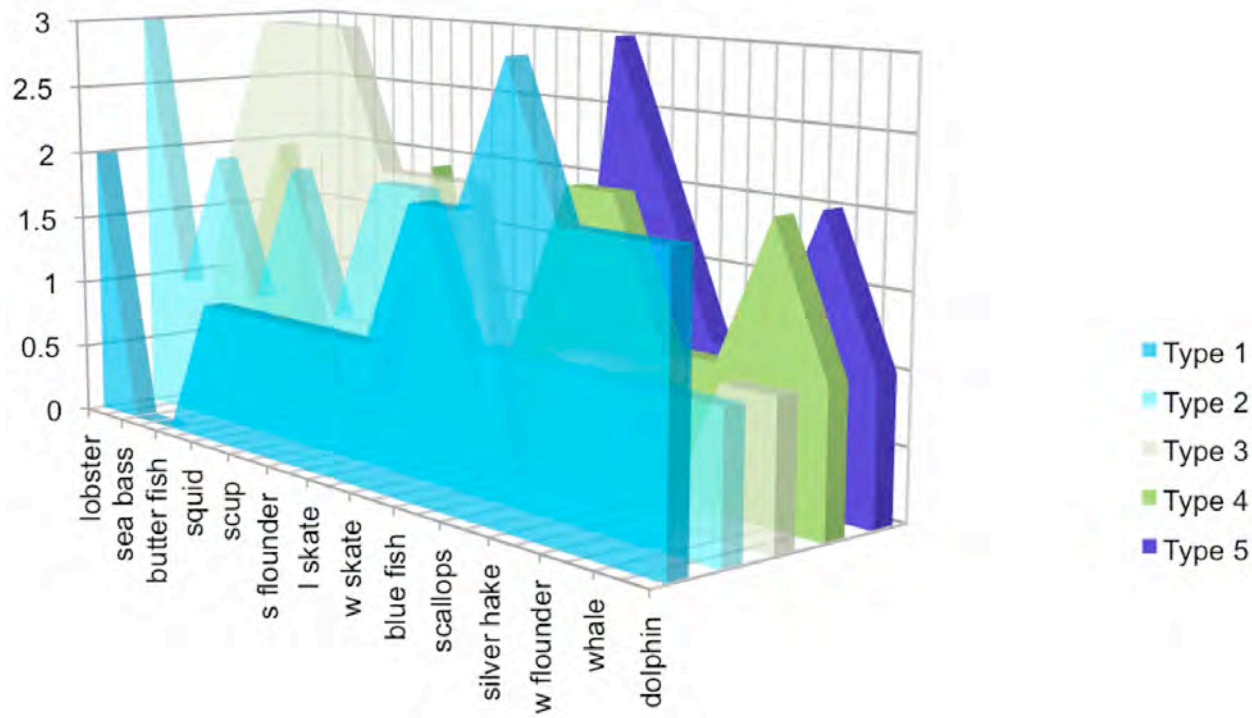


Figure 10: Diagram representing the biodiversity index –level 1—of each cluster (Type 1 to 5) for Fall, in terms of original variables. The index represents the whole area defined by each species sub-index, varying along a discrete scale 0 to 3.

Mammals are present as well, Whales and Dolphins, and the migratory Bluefish. Dolphins have been shown to follow upwellings (Thompsen, 2010). In the present case, they might be used as tracer of the oceanographic limit between Block Island Sound and Rhode Island Sound.

Table 3: Definition of each cluster in terms of geophysical variables. Each geophysical variable is defined by a relative score based on its mean value in the cluster as compared to its global probability distribution. Scale 1 to 4.

Geophysical characteristics of each cluster					
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Depth	4	1	0	1	4
Slope	1	2	3	2	0
Roughness	1	3	4	2	0
Phi median	1	2	3	1	2
SST	4	1	0	1	4
Stratification	4	1	0	2	4

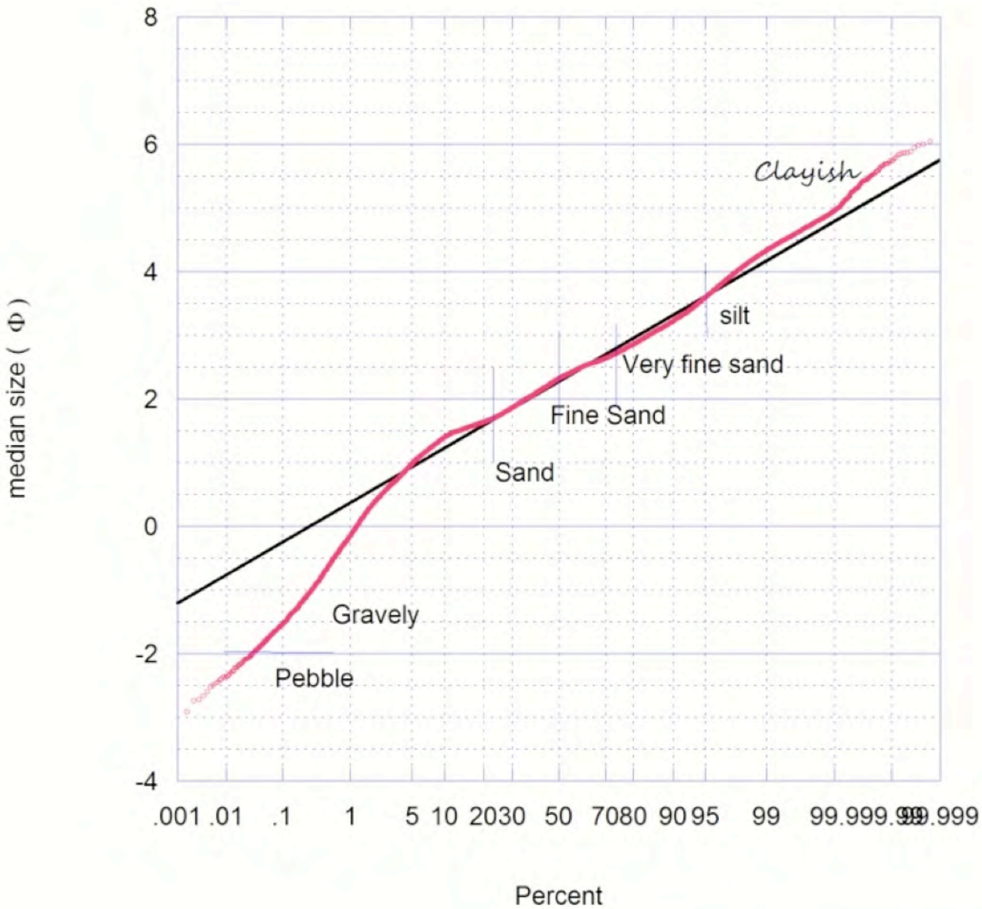


Figure 11: Grain size probability distribution (in phi unit) in the SAMP area.

6 Fall Season Geophysical Typology

In order to have a general overview of the geophysical environment and therefore understand better the relationship between the ecological clusters and the environment, a similar PCA-CA analysis was applied to selected geophysical variables: water depth (m), bottom slope (maximum slope in a 200 by 200 m cell (deg.)), bottom roughness (standard deviation of slope on 1000 m radius (deg.)) , median grain size (phi units) (phi=negative logarithm to the base 2 of the particle diameter in Millimeter), SST at 27 m (deg.), and stratification (buoyancy frequency squared, 10^{-4} s^{-2}]). As before, each of these variables is re-interpolated onto the 200 by 200 m grid and mapped over the SAMP area. These maps are given in Appendix A. The probability distribution of each of these variables is presented hereafter in a cumulative representation, so it is easy to relate each quartile of the distribution to the corresponding value of the variable. For example the median or 50 % of the distribution of the median grain sixe (in phi value) is above 2, defining fine sand. The indexing method defined above, already used to help in the cluster interpretation, is based on comparing the mean cluster value of each variable to that in their general probability distribution for the entire area, in terms of quartile or percentile. In summary, the indices relate the clusters to the relative value of the distribution, in terms of quartiles or percentiles, and the probability distributions relates the index to the true value of the variables.

Figures 12 to 15 show probability distributions as compared to the expected normal values. We see that grain size in phi unit, depth, and sea surface temperature are fairly normally distributed. Slope and roughness are log-normal and their value is thus log-transformed for the PCA-CA analysis.

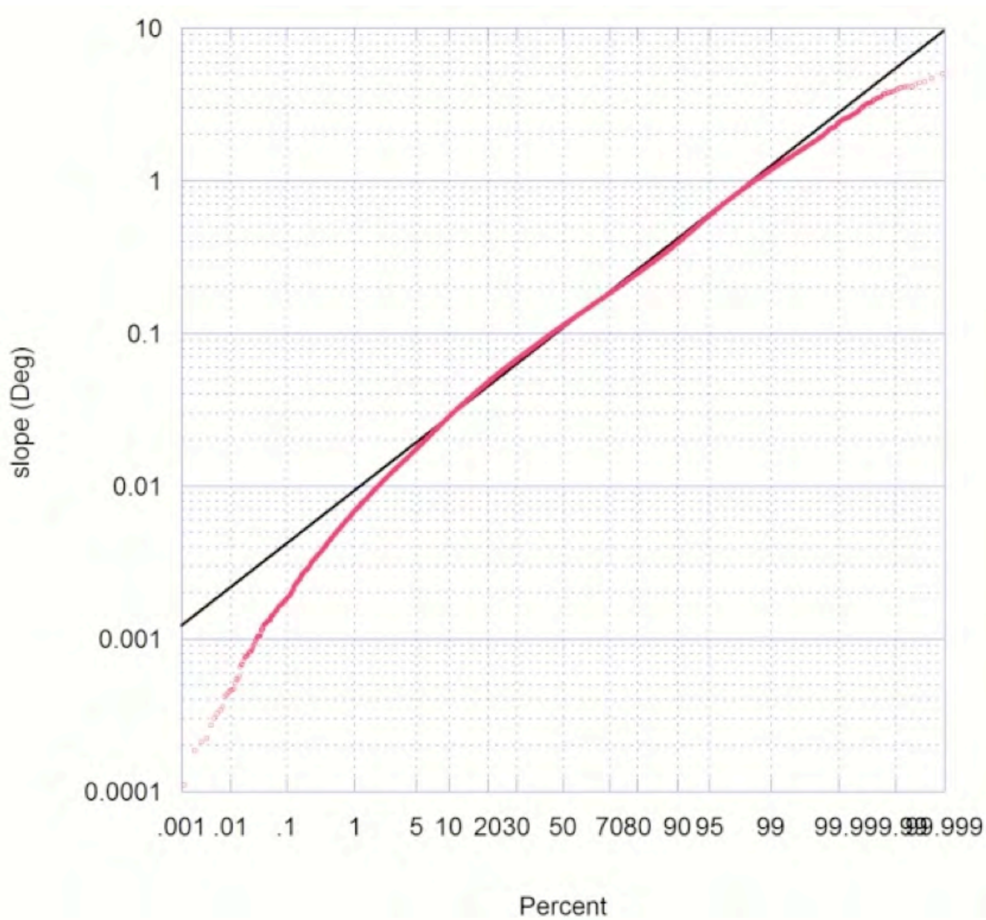


Figure 12: Slope (deg.) probability distribution in the SAMP area (log scale)

As for the ecological analysis, results of the PCA-CA analysis for the geophysical variables in Figure 16 reflect the onshore-offshore gradient, the relative oceanographic dichotomy between Block Island and Rhode Island Sound, and the geological and sedimentological variance. Cluster 4 regroups deeper warm stratified waters over a smooth sandy bottom. It is bordered by Cluster 1, in a Rhode Island Sound intrusion towards the shore, regrouping intermediate waters between the warm stratified offshore waters and the cooler mixed coastal waters, but also corresponding to the mostly clayish bottom of the area covering the relatively smooth and flat bottom of Rhode Island Sound. Cluster 3 regroups shallower well-mixed cold waters above rough and steep silty bottom. Cluster 2 regroups, shallow to medium depth waters, with mixed waters over a gravely bottom.

Table 4:Geophysical clusters definition in term of original variables scores (scale 1 to 5). Scores are based on the relative value of the cluster mean value of each variable compared to the global probability distribution of each variable.

	c3	c4	c2	c1
Depth	0	5	1	1
Slope	4	1	2	2
Roughness	5	0	2	1
phimedian	3 =silty	1=sand	0 =gravely sand	5 =clayish
SST	0	4	1	1
Statification	0	5	1	1

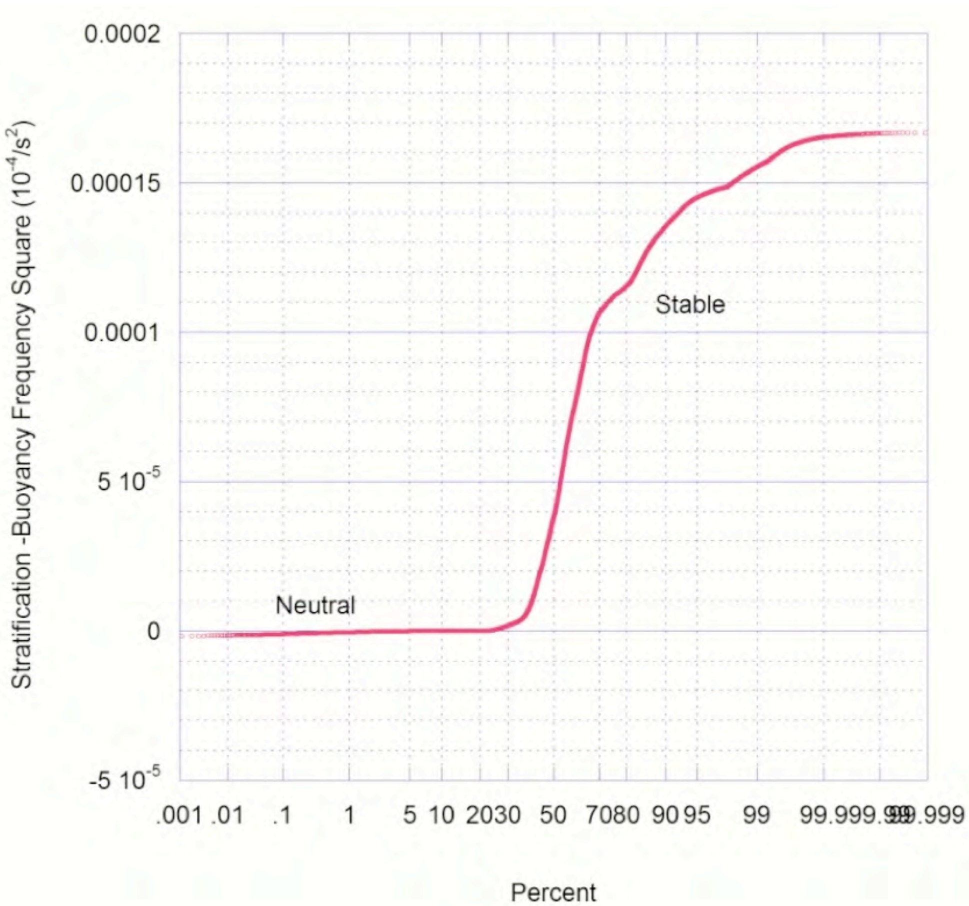


Figure 13: Fall bottom (27 m) stratification (buoyancy frequency fquare (10^{-4} s^{-2})) probability distribution in the SAMP area . Data provided by Codega and Ullmann (2010).

The similar patterns of the geophysical and ecological clusters, which were independently derived, is striking and validates the ecological typology, in the sense that the ecological stuctures correspond to geophysical structures, as could have been expected.

7 Socio-ecological typology for Fall

In a final analysis, we introduce the socio-economic domain by adding the "services" in the analysis: the fisheries use, and mobile, fixed and recreational gears. These are combined into a fishing index (linear sum) quantifying the fisheries use on a scale 1 to 10 (identical method as biodiversity index for scaling).

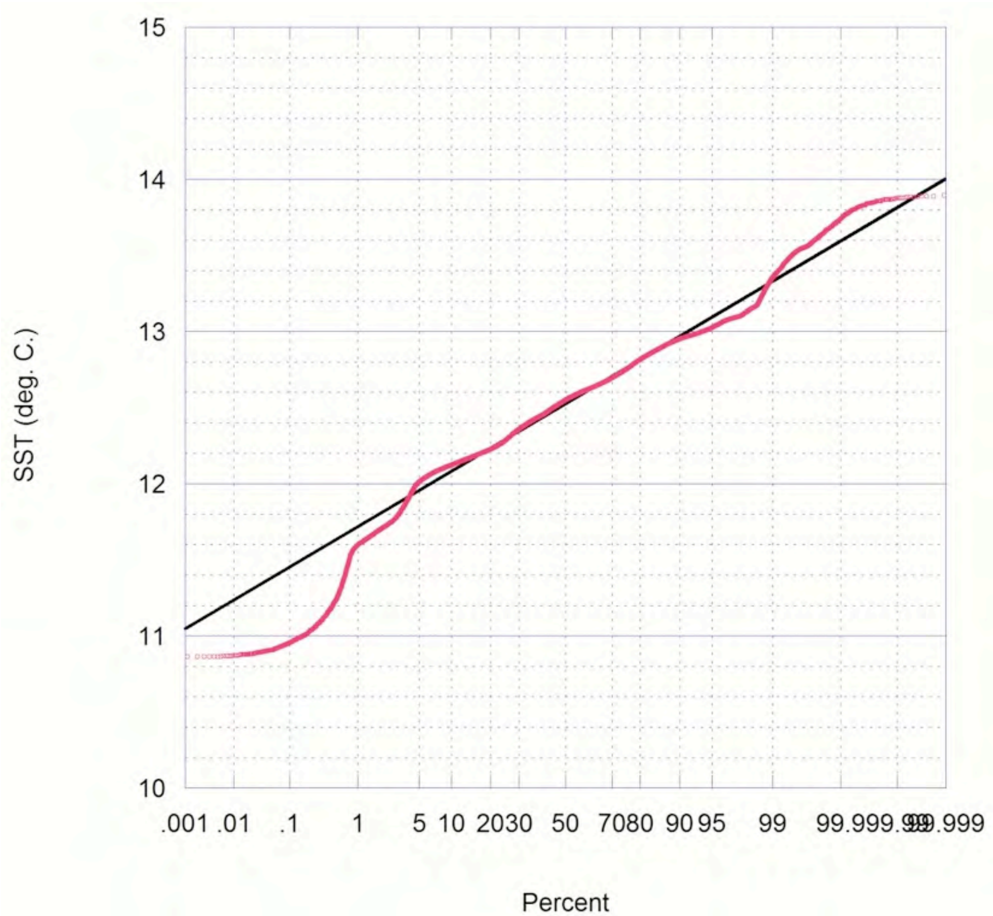


Figure 14: Probability distribution of Fall Sea Surface Temperature (SST) in the SAMP area. Data provided by Codega and Ullman (2010).

Re-doing the ecological analysis when adding the fishing index as a new variable leads to a similar pattern, but two clusters are now dominated by fisheries use, Cluster 3 with a service index of 9, and Cluster 6 with a fishing index of 5, regrouping the areas most intensively used by mobile and fixed gears. Cluster 3 regroups the recreational area in rocky bottom shallow waters around Block Island and in the center of Rhode Island Sound, around Cox's Ledge. Ironically, Cluster 3 is characterized by a low biodiversity index grouping rocky species such as Sea Bass. It is clear that rocky species are hard to catch and are not correctly statistically represented in the surveys. Striped Bass for example was eliminated from the analysis because it was under-represented (based on our assumed criterion). Clusters 2 and 5 are the shallow water sub-regions, opposing smooth and rocky bottom species. Clusters 4 and 7 are the deep water clusters, differing by their fisheries use. According to our fisheries data, Cluster 7 is fairly used and Cluster 4 is not. This might be due to a lack of data in this area, since most of it is outside the SAMP area. In addition, Cluster 1 regroups an assemblage of high diversity and appears at the eastern border of the area in relatively shallow water, starting at the tip of the southwest shoal and extending northward, but also very punctually at the southeast end of Block Island state Waters. This specific spot corresponds to an area of higher biomass and might reflect the known convergence of currents around the southeast tip of Block Island State Waters. This hypothesis needs to be further investigated.

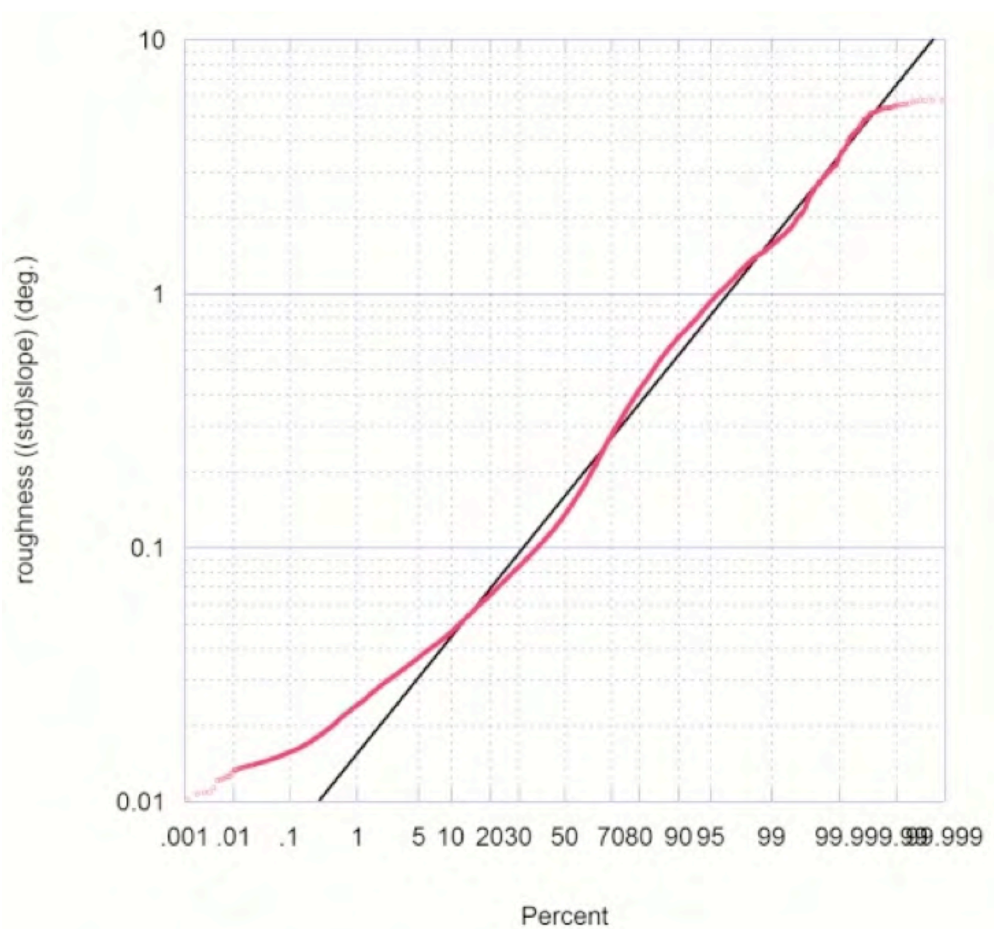


Figure 15:Bottom roughness probability distribution in the SAMP area defined as the standard deviation of the slope in a 1000 m radius (log scale). Data provided by J.King (2010)

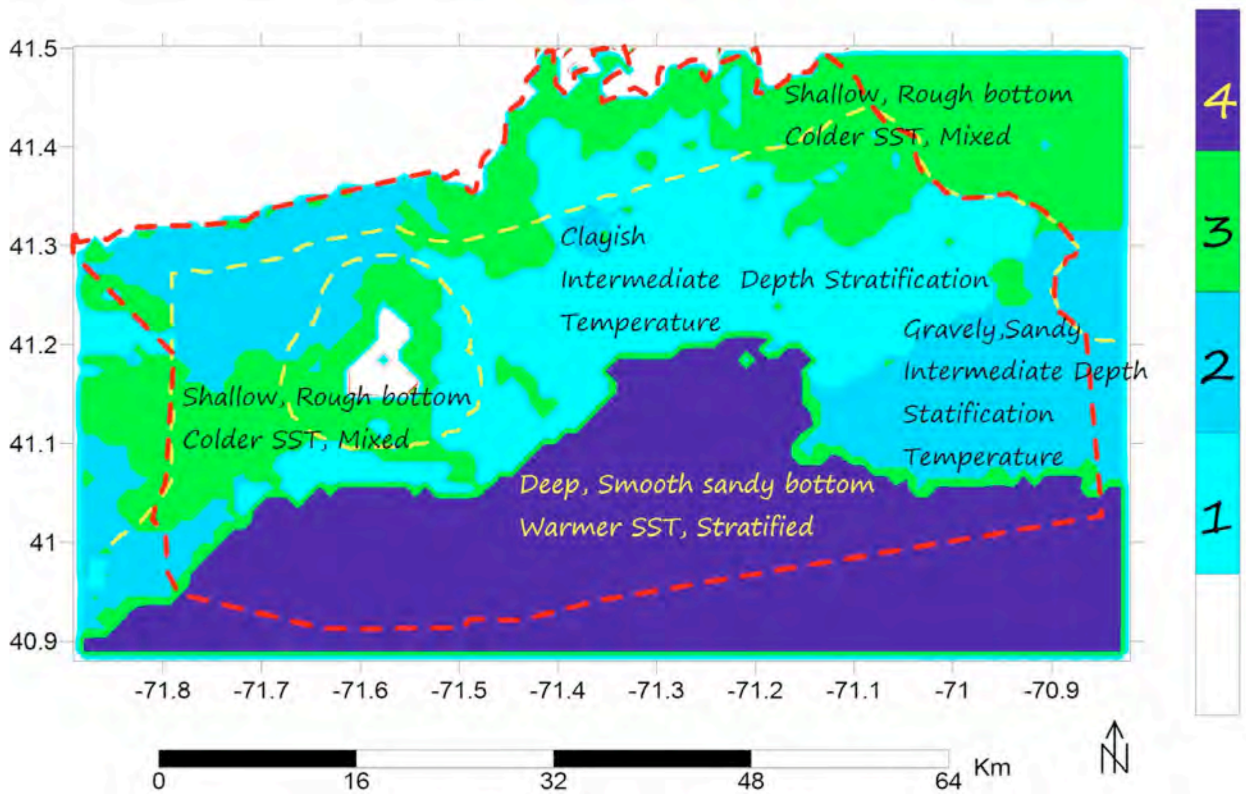


Figure 16 : Seasonal geophysical environment typology for fall season, based on PCA-CA analysis of the 6 geophysical variables in the SAMP area.

8 Conclusions

We applied a PCA-CA analysis method to multivariate ecological/service, and independently geophysical data. As expected from the literature, the method proved to be robust in identifying homogeneous areas among a large set of multivariate spatial data. The comparison of the ecological (clusters) with geophysical sub-regions allows to interpret these sub-regions in terms of habitats, which *a posteriori* justifies the methodology. The additional step of including the socio-economical system through fisheries use data is promising, since it clearly identifies among ecological sub-regions, the recreational, mobile and fixed gear fisherman behaviors.

Results of the PCA-CA analysis, consistently, reflect an onshore-offshore gradient and the geological and sedimentological variance. A deep water assemblage is isolated from a shallow water assemblage. The intermediate and shallow waters are separated into two assemblages, reflecting both the oceanographic dichotomy between Rhode Island and Block Island Sound, and the variance in geological deposits. The terminal moraine lying intermittently across the Block Island and Rhode Island Sounds, in particular on the southeast of Block Island and at the tip of Sakonnet point, creates area of high bottom rugosity and clayish sediment, favorable to benthic habitats. Those areas are isolated in homogeneous biodiversity cluster representing an homogeneous fish and mammals assemblage.

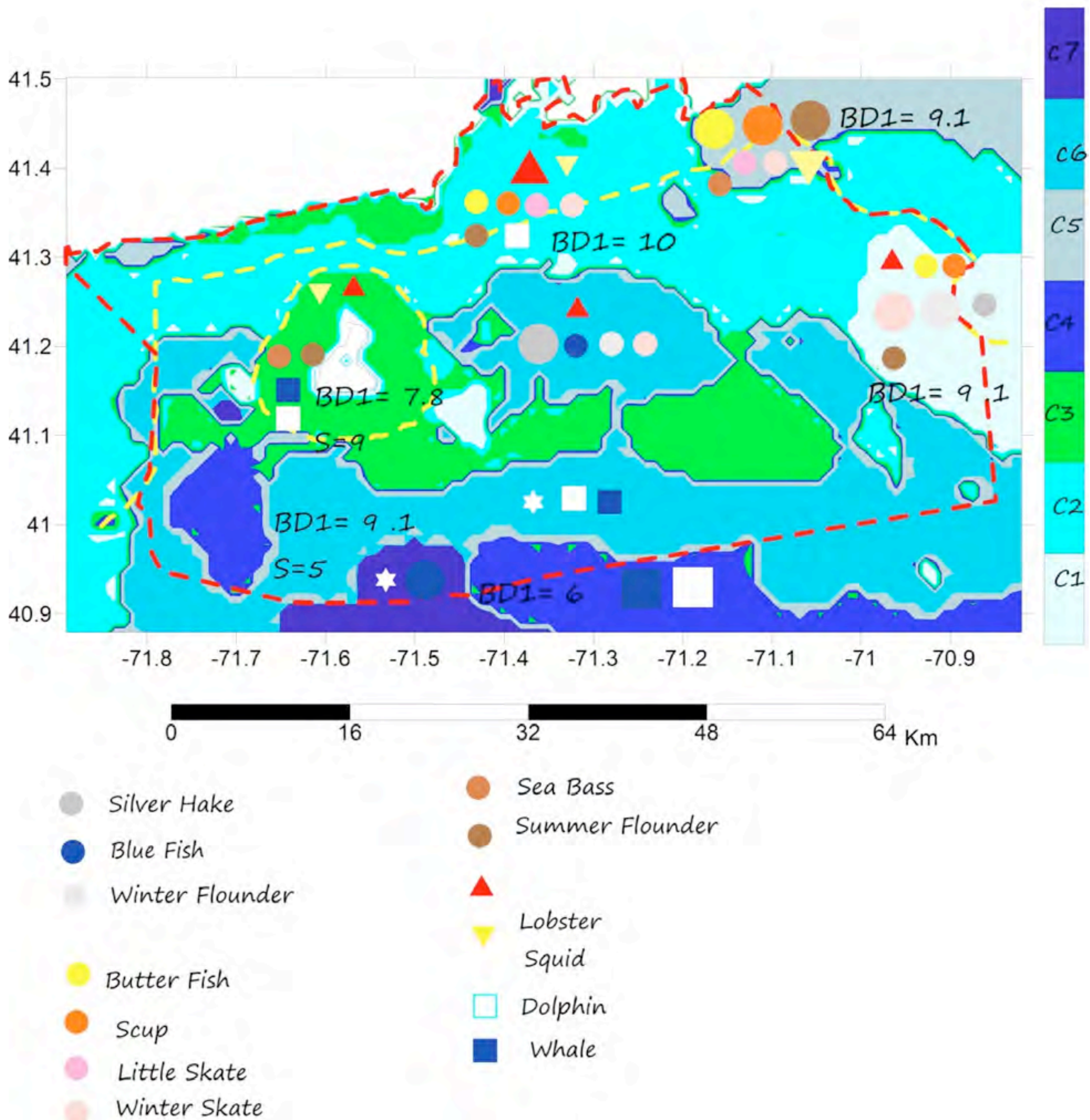


Figure 17: Seasonal ecological and service typology for Fall , based on PCA-CA analysis of the 6 geophysical variables in the SAMP area.

The Biodiversity index is at this point developed for descriptive purpose, and is specific to this area only. However, this step shows that this index is not sufficient to discriminate the area. Identical numbers correspond to different assemblages. Furthermore, the low index value in the high bottom rugosity area defined by Cluster 3 in the Ecological and Services Typology is questionable, since it is antagonistic to the fishermen behaviors. This either reflects an underestimation of the biodiversity in the sampling, or a bias in fisheries data obtained from fishermen, which is possible since those are only binary data.

This PCA-CA based Marine Management Tool developed here proved to be promising in identifying sub-regions, but it is still at a stage of development. Future major stages in furthering the development of this tool are:

- Adding ecological and services variables to represent more accurately the ecological and social environment, and therefore discriminate better the space.
- Developing the method of cluster valuation:
    - The biodiversity and service indices are a first attempt at valuation and follow up work should involve using and comparing the various standards, or newly developed indices (Shannon 1947; Derous, 2007; Borja et al. 2007; Spellerberg and Fedor, 2003).
    - The concept of valuation should relate the valuation criteria to the different organizational levels of biodiversity, such as population, community, ecosystem, which means discriminating migratory species passing though the area, from species living in symbiosis with others, or species associated to a particular geomorphologic feature, or related to a particular oceanographic process, such as upwelling (Derous, 2007).
    - Address the concept of rarity.

- Assess the uncertainty of the groups isolated by the clusters due to the uncertainty in the data and discuss the clusters borders in those terms: rigid or fuzzy borders.
- Address the dynamic aspect of those sub-regions by introducing time series of the variables rather than mean values in input.

Addressing these questions is subject to data availability, but we are hopeful that in a near future we can introduce birds and benthos data in the ecological or Supporting Services category, as well as quantitative fisheries data in the Service Category, or Provisioning Services and Cultural Services Categories, according to the nomenclature of Table 1.

Appendix A : Maps of geophysical/geological and oceanographic data in SAMP area

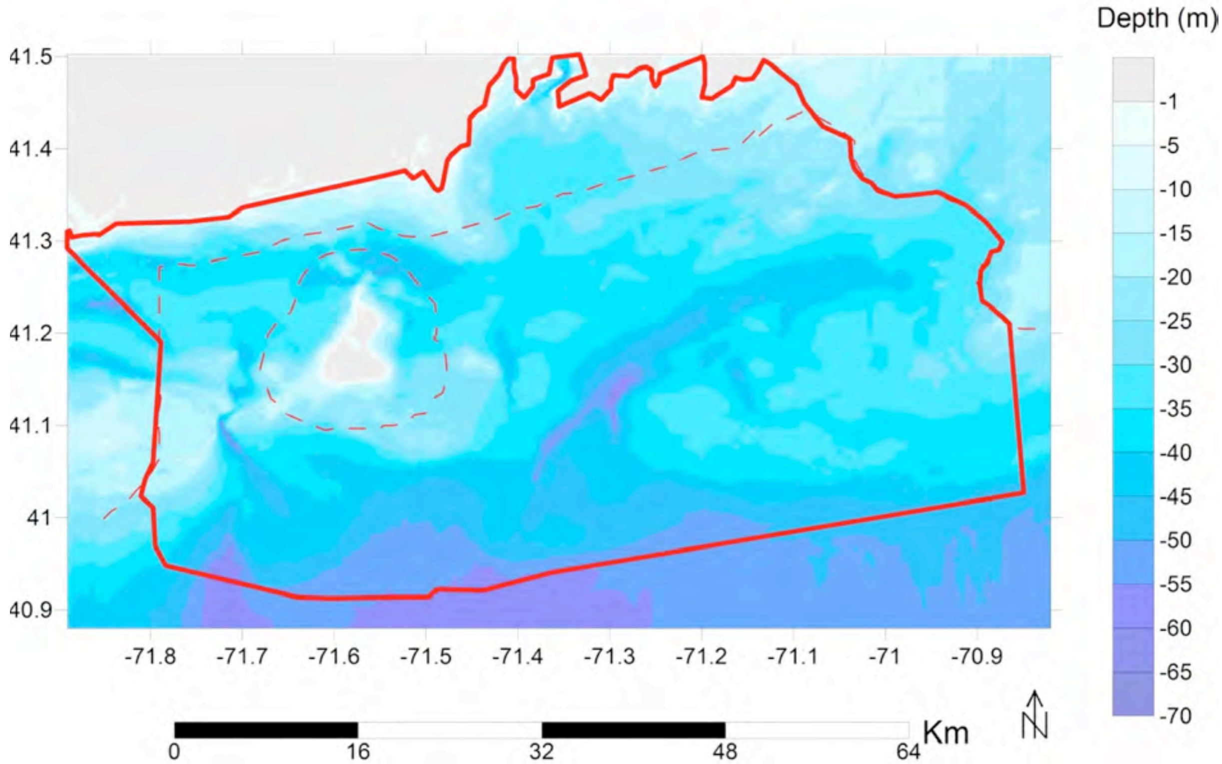


Figure 18: Bathymetry in the SAMP area

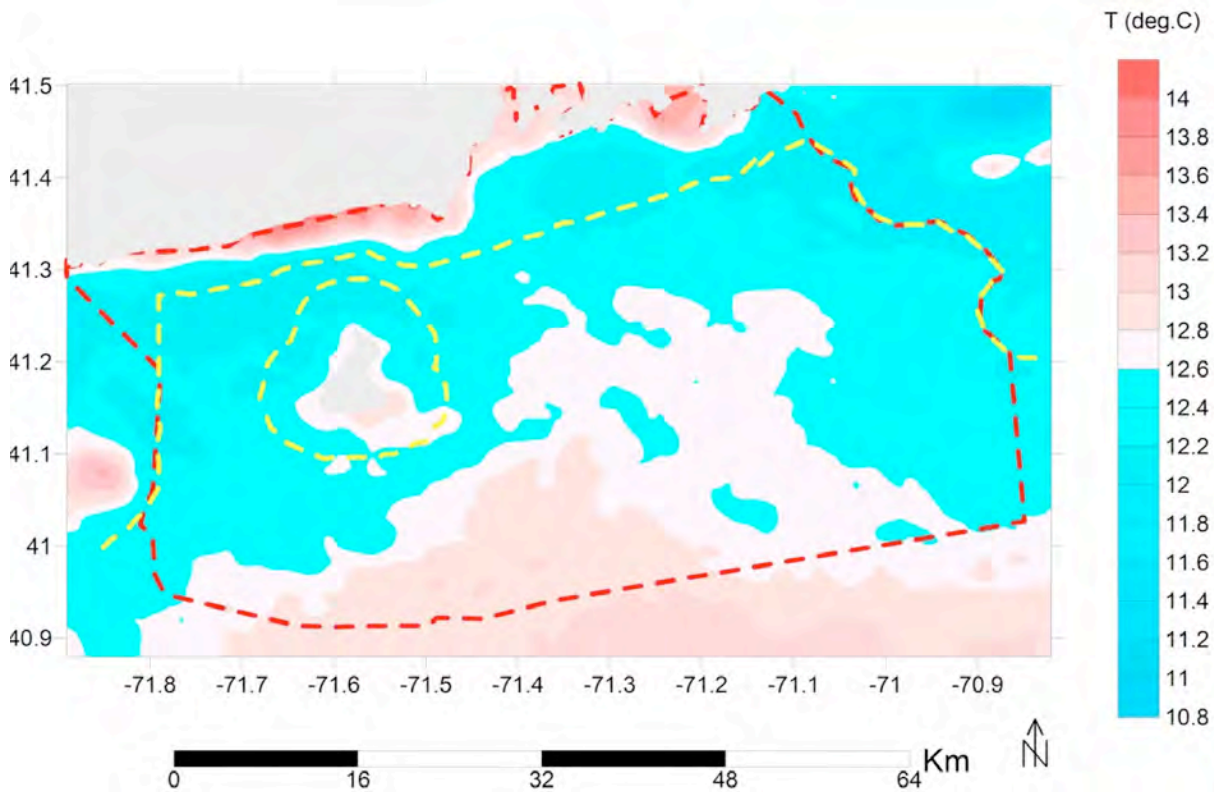


Figure 19 Sea Surface Temperature (SSTD) reinterpolated on a 200 by 200 m grid. Data from Codega and Ullmann (2010)

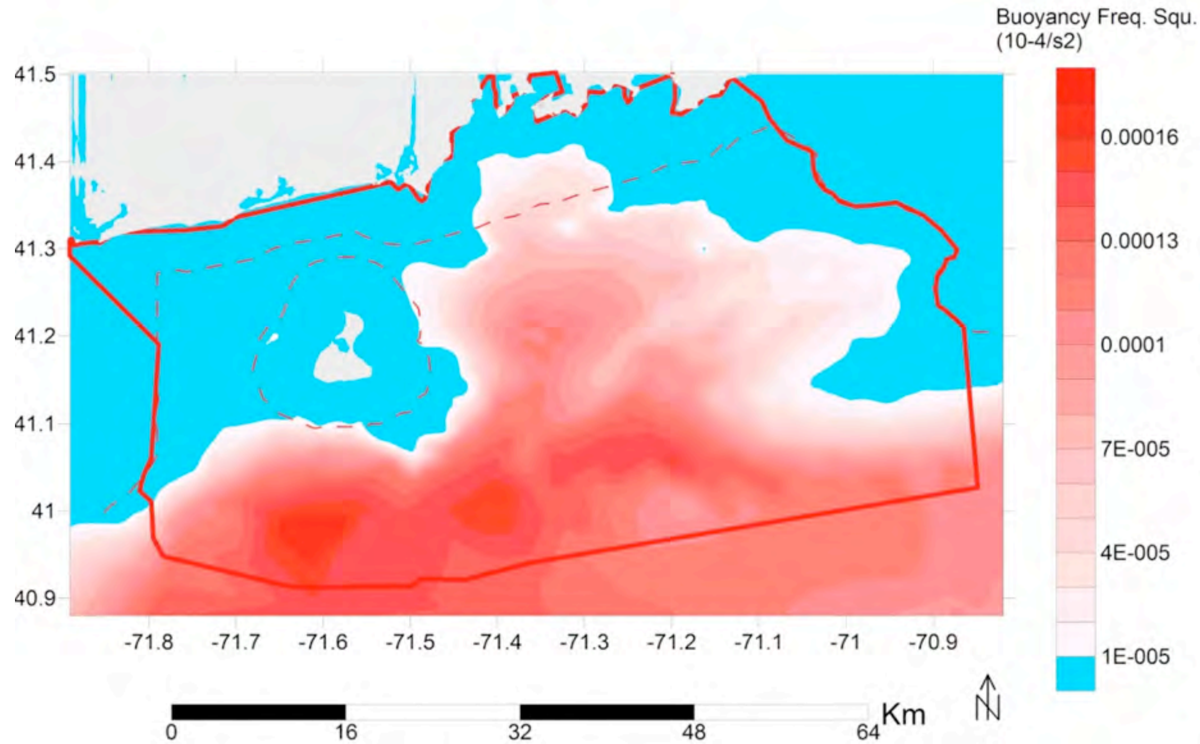


Figure 20: Fall water stratification in buoyancy frequency square ($10^{-4}s^{-2}$). Data obtained from Codega and Ullmann (2010) and reinterpolated on the 200 by 200 m grid

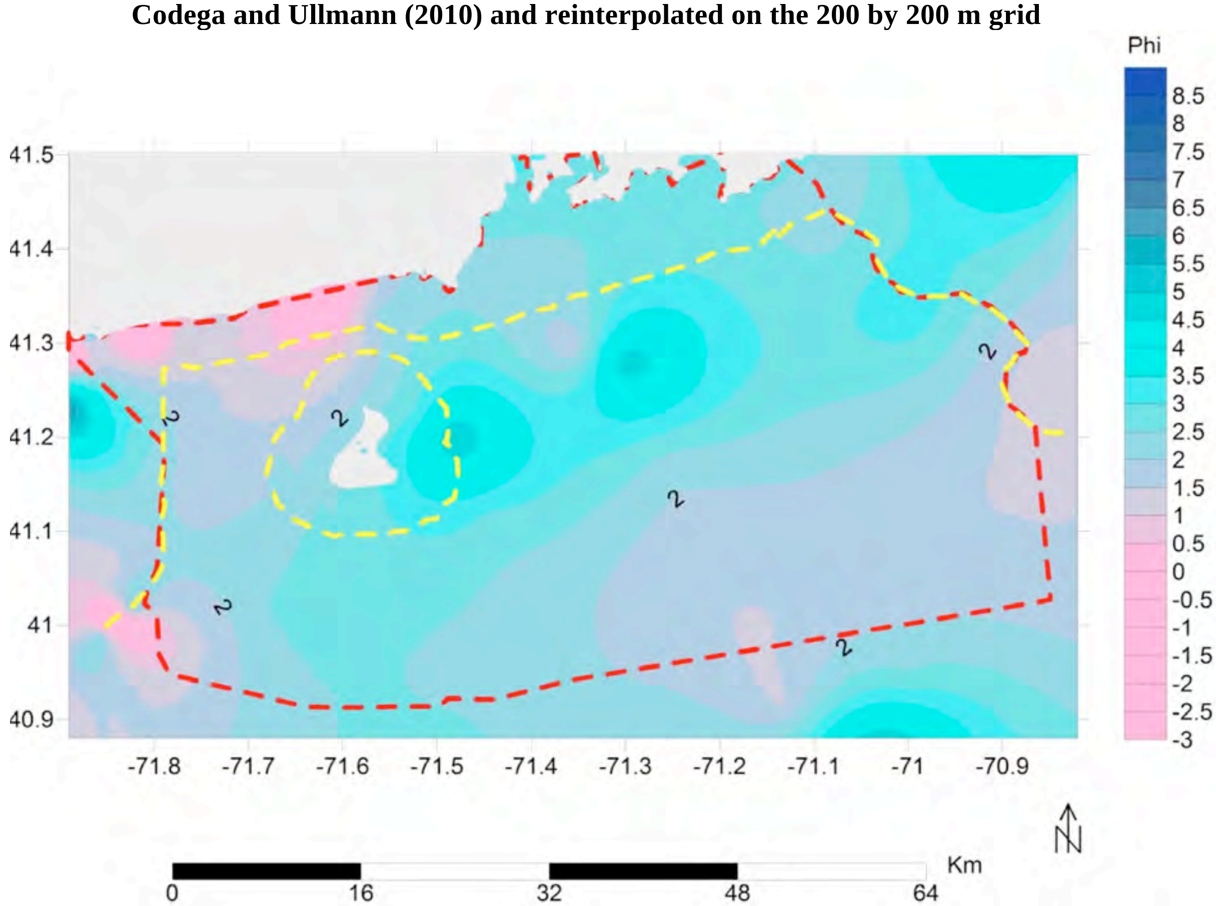


Figure 21: Sediment grain size distribution in phi units

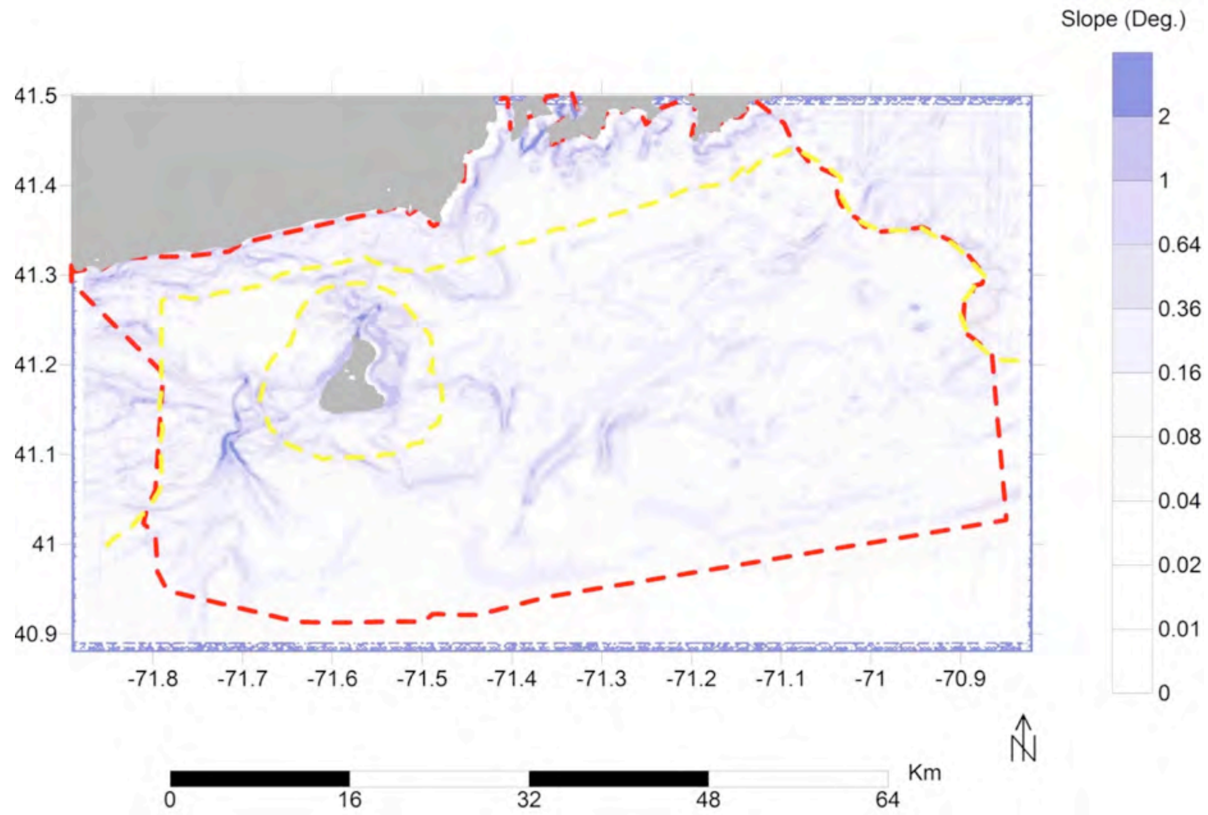


Figure 22 : Maximum slope at each grid cell (deg.)

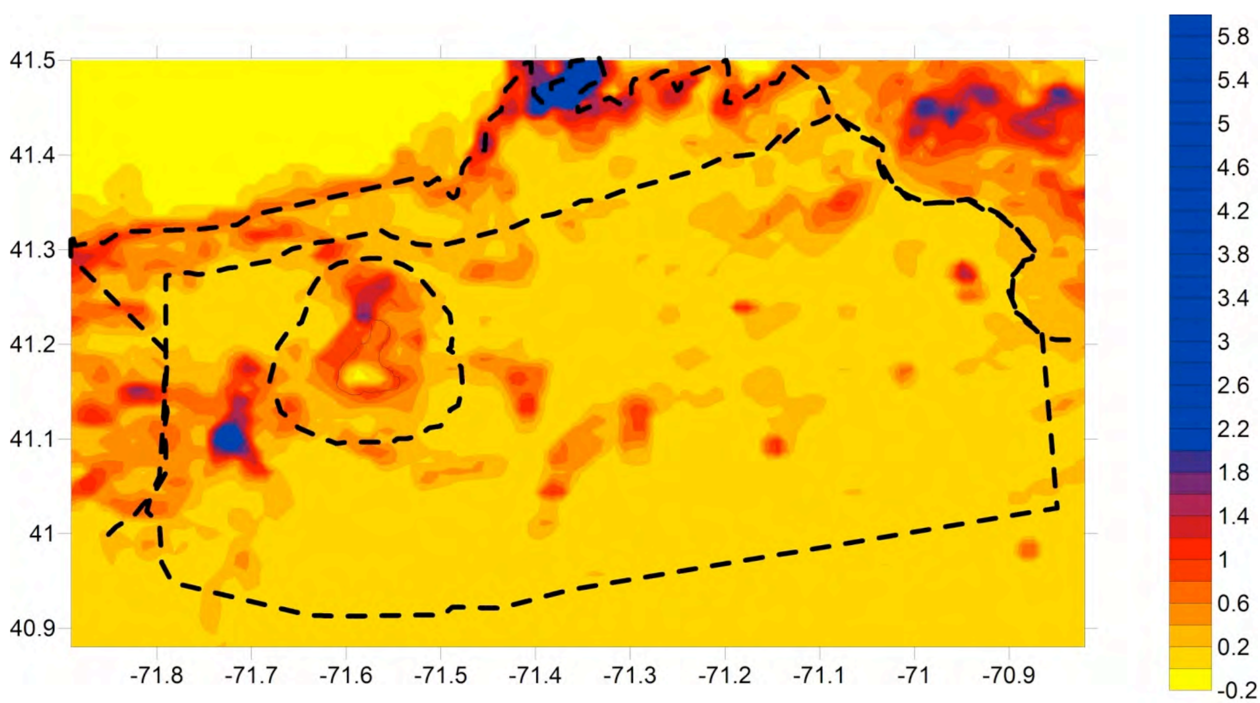
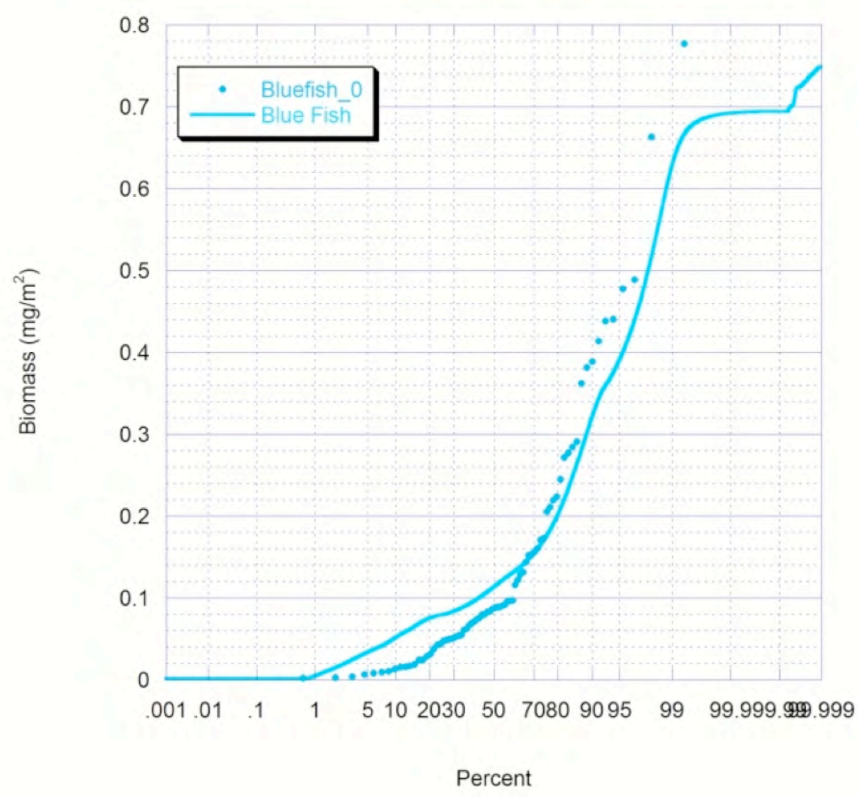
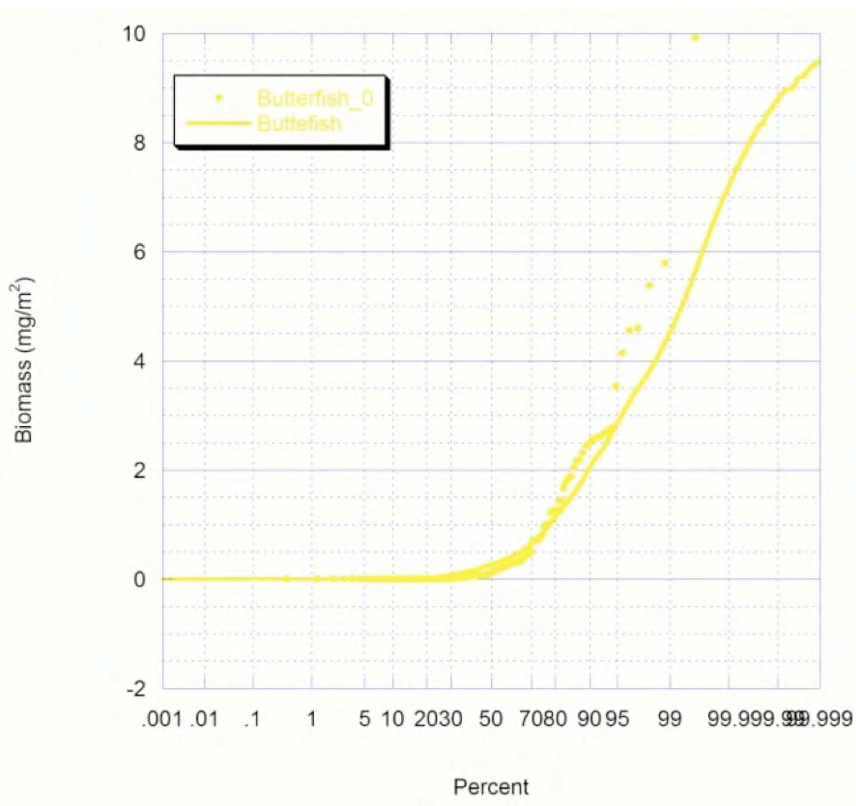
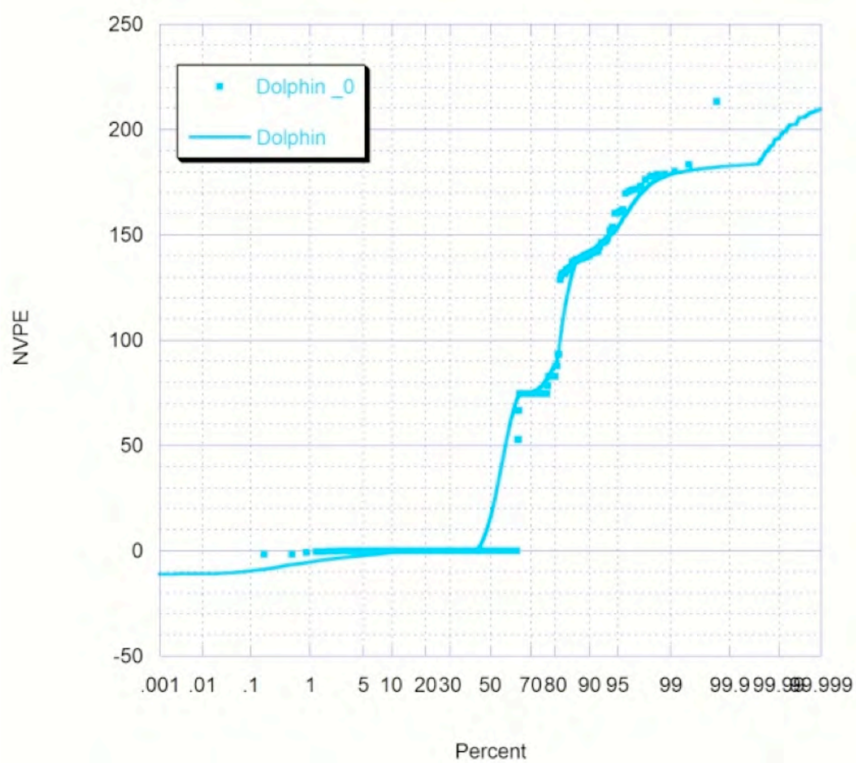


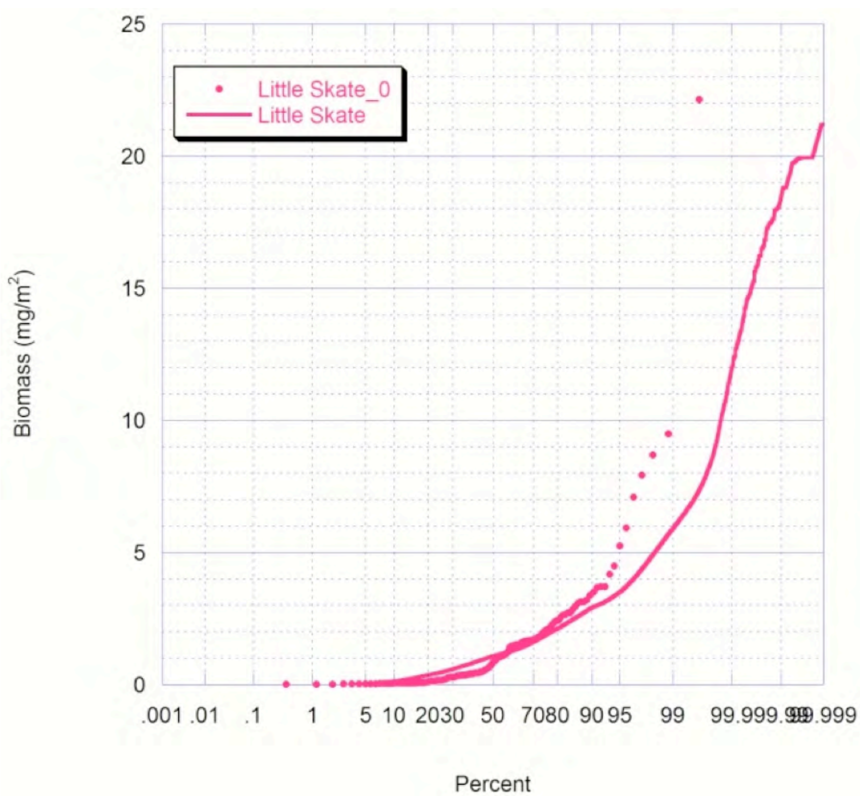
Figure 22: Surface roughness defined as the slope standard deviation on a 1,000 m radius. Data provided by John King (2010)

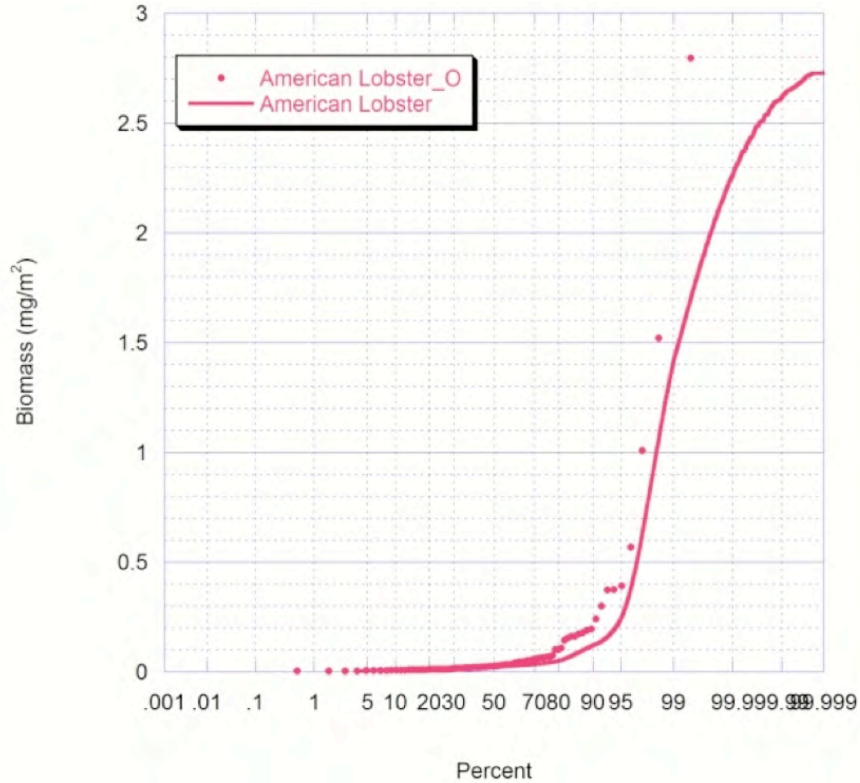
Appendix B: Statistical distributions of ecological variables



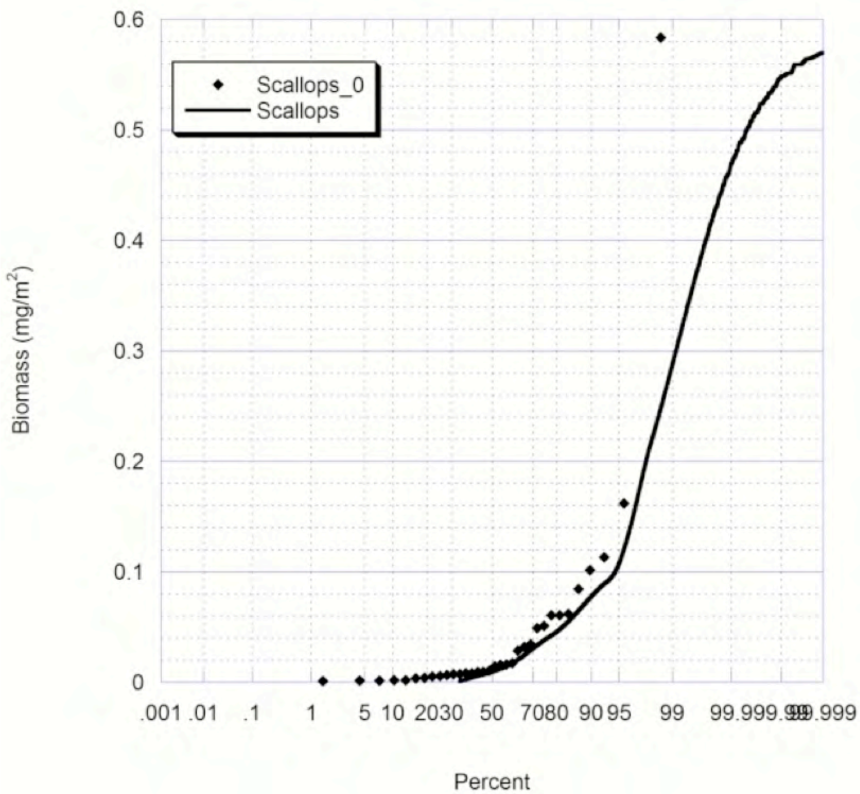



Dolphin _0
Dolphin
NVPE
250
200
150
100
50
0
-50
.001 .01 .1 1 5 10 2030 50 7080 90 95 99 99.9 99.99 99.999
Percent

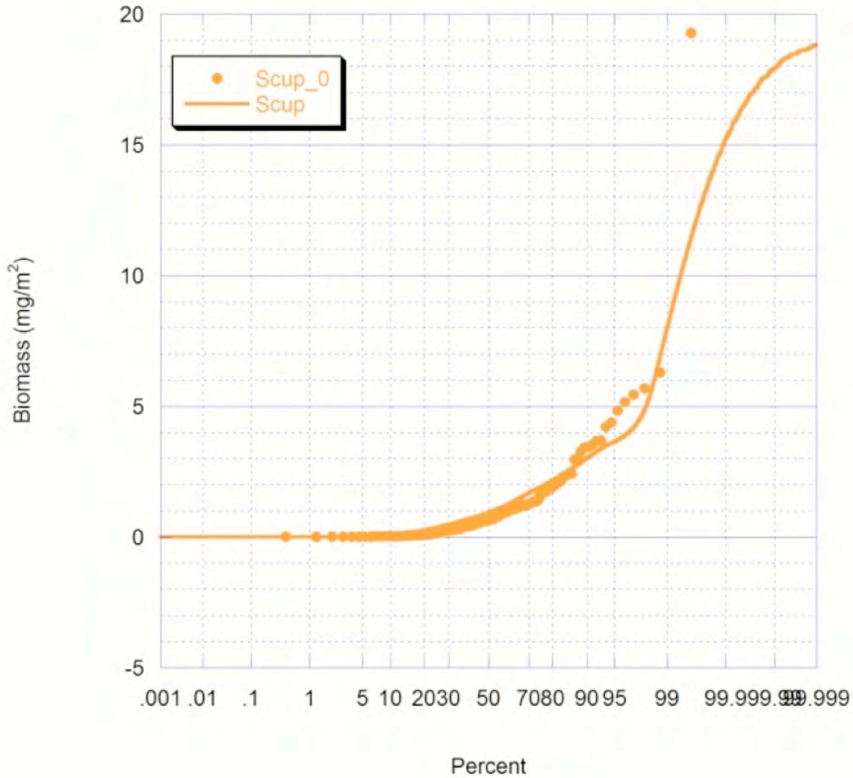

Little Skate_0
Little Skate
Biomass (mg/m2)
25
20
15
10
5
0
.001 .01 .1 1 5 10 2030 50 7080 90 95 99 99.9 99.99 99.999
Percent

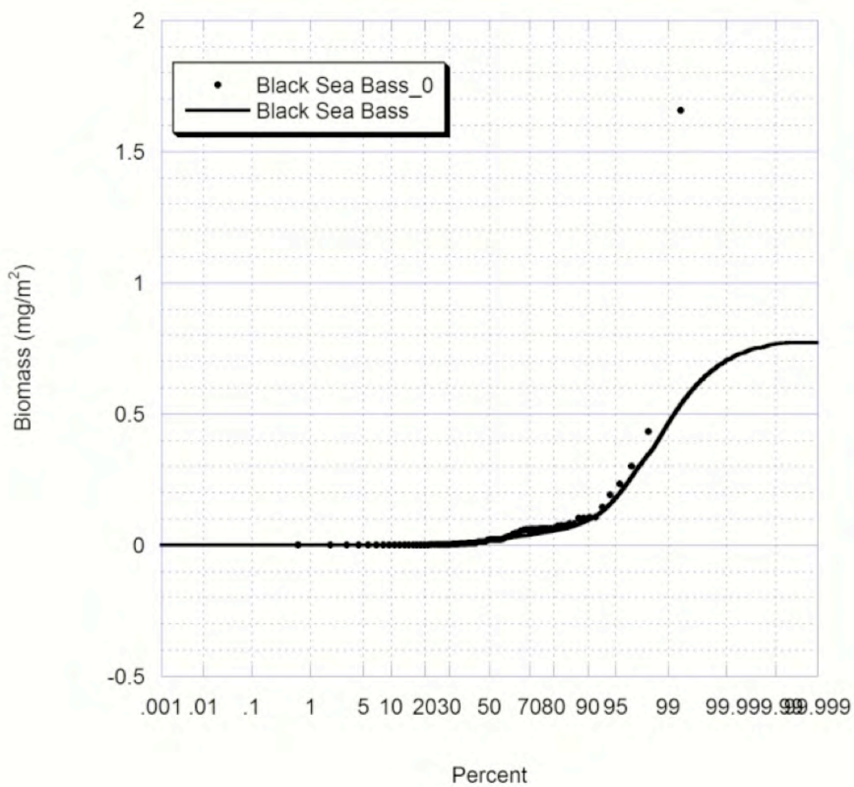


American Lobster_O
American Lobster
Biomass (mg/m²)
Percent
3
2.5
2
1.5
1
0.5
0
.001 .01 .1 1 5 10 2030 50 7080 90 95 99 99.999.99 99.999



Scallops_0
Scallops
Biomass (mg/m²)
Percent
0.6
0.5
0.4
0.3
0.2
0.1
0
.001 .01 .1 1 5 10 2030 50 7080 90 95 99 99.999.99 99.999


Scup_0
Scup
Biomass (mg/m^2)
20
15
10
5
0
-5
.001 .01 .1 1 5 10 2030 50 7080 90 95 99 99.999.9999.999
Percent


Black Sea Bass_0
Black Sea Bass
Biomass (mg/m^2)
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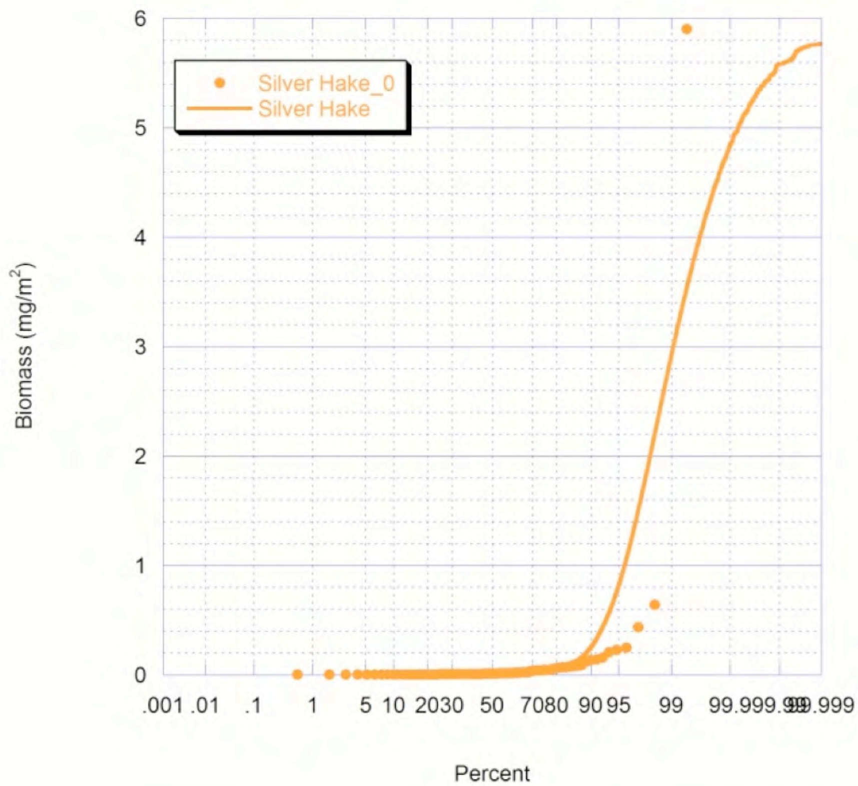
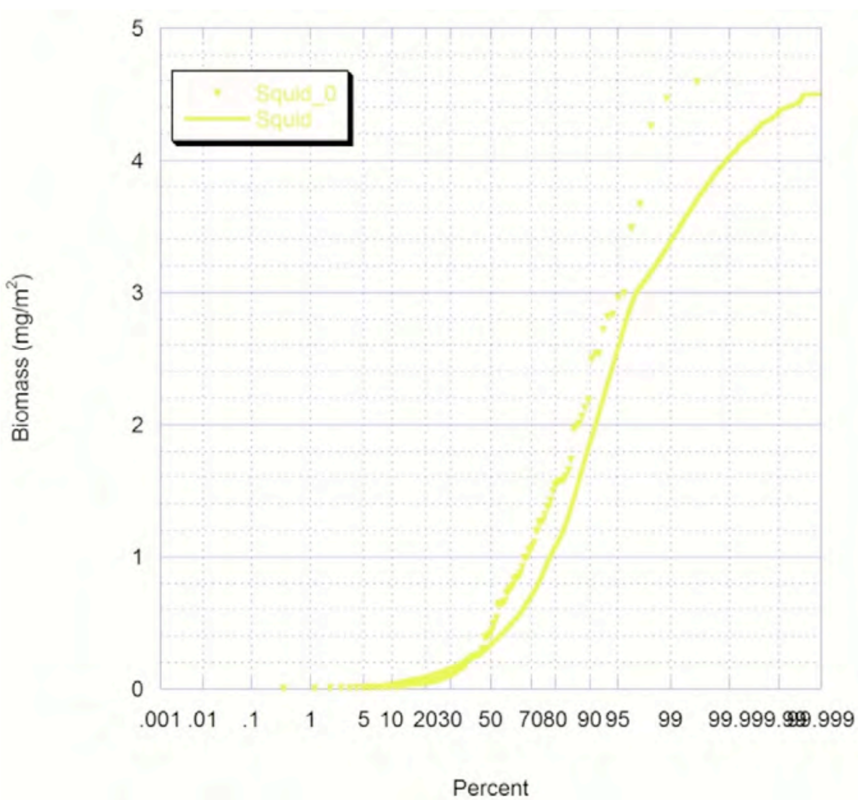
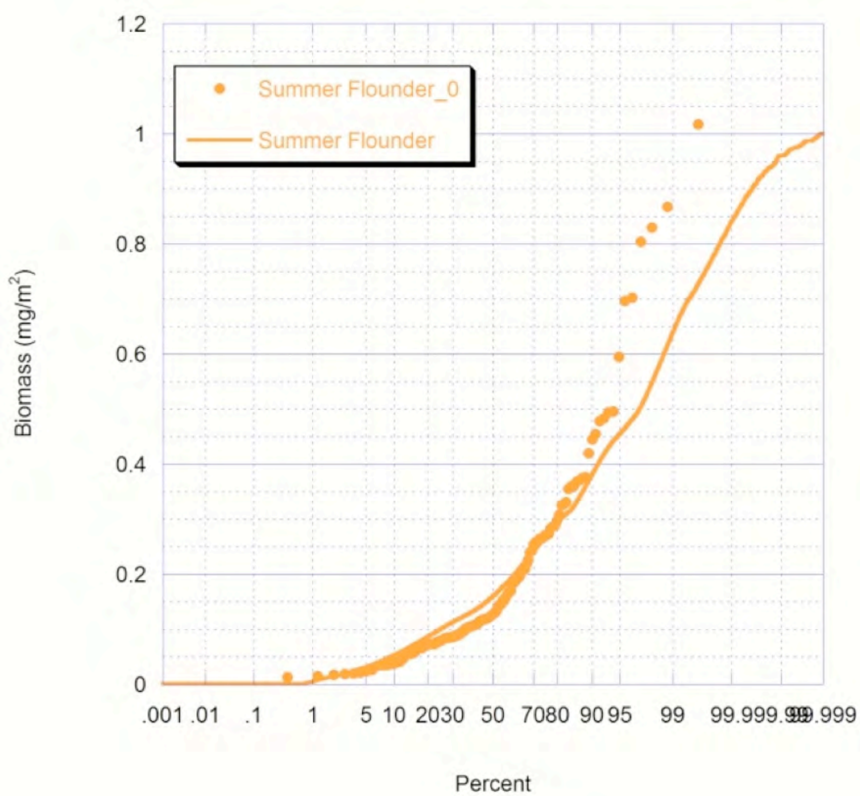
1
0.5
0
-0.5
.001 .01 .1 1 5 10 2030 50 7080 90 95 99 99.999.9999.999
Percent


Silver Hake_0
Silver Hake
Biomass (mg/m^2)
6
5
4
3
2
1
0
.001 .01 .1 1 5 10 2030 50 7080 90 95 99 99.999.99 99.999
Percent


Squid_0
Squid
Biomass (mg/m^2)
5
4
3
2
1
0
.001 .01 .1 1 5 10 2030 50 7080 90 95 99 99.999.99 99.999
Percent


1.2
1
0.8
0.6
0.4
0.2
0
Summer Flounder_0
Summer Flounder
Biomass (mg/m^2)
.001 .01 .1 1 5 10 2030 50 7080 90 95 99 99.9 99.99 99.999
Percent

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