Spatial pattern in the Eastern Bering Sea: An application of spatial analysis to groundfish abundance along the Bering Sea outer continental margin

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Abstract: As place-based frameworks are increasingly applied to fisheries management, researchers are faced with the need to define ecosystem units and collect data in a manner that will meet this management need. Place-based management approaches, such as ecosystem-based management and marine spatial planning, are explicitly tied to spatial considerations and rely on an understanding of the spatial arrangement of elements within the system and how elements interact. I explore the utility of spatial pattern analysis and spatial statistics for understanding the distribution of marine resources. I focus on the upper shelf and outer slope region of the Eastern Bering Sea continental margin. This region is highly heterogeneous in terms of geomorphology of the shelf break and system of canyons that incise the shelf. I used slope and aspect to divide this region into shelf and slope geomorphic zones and facets and divided this region into a northern and southern portion to explore spatial pattern at a range of scales. I quantified structural heterogeneity with a shape index and surface roughness metric. I used groundfish catch per unit effort (CPUE) trawl survey data to describe and quantify the degree of spatial autocorrelation in this region. I found spatial autocorrelation of groundfish CPUE in the upper shelf and outer slope region of the Eastern Bering Sea continental margin. The clustering pattern was dominated by low-value clustering at the global level. At the local level, low-value clusters were confined to the southern portion of the study area and high-value clusters varied spatially and temporally. Outliers were most commonly found in close proximity to the shelf-slope break. This explicitly spatial method demonstrates the feasibility of this approach in fisheries management.

INTRODUCTION

Place-based marine management frameworks, such as ecosystem-based management (EBM) approaches, have been proposed by institutions and governmental bodies as a means to sustainably manage coastal and marine resources (EPAP, NMFS 1999; POC 2003; USCOP 2004). EBM is an integrated approach to management that recognizes human linkages with ecosystems and considers interactions within and among systems and across spatial and temporal scales (Leslie and McLeod 2007). EBM explicitly acknowledges the complexity of human and ecological systems and the emergent properties that arise from these underlying complexities. EBM for fisheries management is geographically specific, adaptive, considers ecosystem knowledge and uncertainty, takes into account external influences, and serves to balance societal objectives (Sissenwine and Murawski 2004). Tools have been developed to meet these goals including spatially explicit management frameworks such as marine protected areas (MPAs) and marine spatial planning (MSP). MPAs are spatially discrete marine areas in which restrictions on human use are established in order to rebuild stocks and encourage recovery of overexploited areas, protect habitats and ecosystem structures, maintain species biodiversity, or preserve culturally significant sites (Browman and Stergiou 2004). MSP is a multi-sectoral approach that brings together stakeholders to make coordinated and informed decisions about how to use marine and coastal resource with the intention of creating comprehensive plans that consider tradeoffs between ocean uses and goals (Ehler and Douvere 2009). Both MPAs and MSP are marine and coastal management tools that combine consideration of the complexity of ecological and socioeconomic systems with explicit reference to the spatial attributes and scales of ecosystems.

The National Oceanic and Atmospheric Administration (NOAA) and the North Pacific Fisheries Management Council (NPFMC) use an ecosystem-based approach to fisheries management in federal waters off the coast of Alaska. This approach incorporates temporal scale through annual and long-term assessments (Livingston et al. 2005); considers interactions within and among fisheries through a single species management approach of annual and seasonal quotas and a multispecies approach of limits on incidental catch and target fishery closures when incidental catch limits are reached for non-target and protected species (Ruckelshaus et al. 2008); and protects habitat through the use of MPAs (Witherell et al. 2000). Broader ecosystem interactions between target fisheries and other species are accounted for with diverse tools such as the spatial and temporal allocation of walleye pollock (*Theragra chalcogramma*) and Atka mackerel (*Pleurogrammus monopterygius*) to manage fishing pressure on sources of food for Steller sea lions (*Eumetopias jubatus*) (Witherell et al. 2000). Other management measures in the Bering Sea include limiting fishing and transiting near marine mammal rookeries and haul-outs; reducing bycatch by establishing bycatch limitation zones for snow, king and tanner crab and implementing salmon and herring savings areas when prohibited species catch limits are reached; and protecting blue king crab (*Paralithodes platypus*) habitat with the Pribilof Islands Habitat Conservation Area (Witherell and Woodby 2005).

Although NOAA and the NPFMC have taken actions to implement an ecosystem-based approach in the Bering Sea, challenges exist. Some are general to the implementation of EBM, such as managing the time lag between stock assessment modeling and decisions on fishery allocations (Methot 2009). Others are specific to regional implementation, such as recommendations to include broader ecosystem objectives in management by considering socially valuable habitats and non-target species in higher and lower trophic levels (Ruckelshaus et al. 2008). Considering broader ecosystem components requires a regional knowledge of the biological resources and the socioeconomic uses of those resources.

The Bering Sea supports valuable and productive commercial fisheries, diverse and rare species, and subsistence needs for Alaskan Natives. Given the use of this region by a variety of stakeholders, managers are challenged to meet stakeholder needs and maintain ecosystem functions. The Bering Sea supports over 400 fish species, of which more than 40 are commercially valuable (Hunt et. al. 2010). Major commercial fisheries have been active in the Eastern Bering Sea since the 1950s, with walleye pollock (*Theragra chalcogramma*) becoming a target in the 1970s and remaining commercially important since that time (Hunt et al. 2010). Other commercially important species such as rockfish and crab have experienced population fluctuations due to natural variability in their life cycles and periods of overexploitation (Hunt et. al. 2010). In addition to substantial fishery resources, the Bering Sea supports diverse seabird and marine mammal species. A number of species found in the Bering Sea are rare or listed as endangered. Such species include short-tailed albatross (*Phoebastria albatrus*) and a number of cetaceans including the bowhead whale (*Balaena mysticetus*), fin whale (*Balaenoptera physalus*), humpback whale (*Megaptera novaeangliae*), North Pacific right whale (*Eubalaena japonica*) and sperm whale (*Physeter macrocephalus*) (NOAA 2011).

The Bering Sea is a dynamic marine system serving as a transition zone between arctic and temperate water bodies and containing high structural complexity along the outer continental margin. The Bering Sea experiences substantial seasonal, annual and decadal oceanographic shifts due to the accumulation, advection and melting of sea ice (Stabeno et. al. 1998 and Macklin et. al. 2002) that drive the spring plankton bloom and annual cold pool formation (Stabeno et. al. 1998 and Hunt et. al. 2010). Shifts in physical forcing by the Pacific Decadal Oscillation (PDO) in 1977 and shifts in polar vortex winds by the Arctic Oscillation (AO) in the 1990s has led to a subarctic maritime climate (Overland et. al. 2005) and more recently, extensive sea ice coverage that favors species at lower trophic levels and extends the summer cold pool (Zador and Gaichas 2011).

The geomorphological heterogeneity of the outer continental margin and system of canyons incising the shelf also contribute to the complexity of the Bering Sea ecosystem. Outer continental margins tend to be dynamic with strong gradients in depth, pressure, dissolved oxygen and substrate stability with high population differentiation and species diversity (Levin and Dayton 2009). Shelf edge canyons, such as those of the Bering Sea, are believed to support higher biomass and productivity than other marine areas (Brodeur 2001). The abrupt slope of marine canyons alters downstream circulation and increases the shelf-slope exchange of water and nutrients (Napp et. al. 2000; Brodeur 2001; Allan and Durrieu de Madron 2009). Research by Mizobata and Saitoh (2004) found that the slope topography and canyon features along the shelf edge affect the formation of anticyclonic eddies along the shelf break, finding that advection by mesoscale features led to increased horizontal mixing. Other processes such as sediment flushing, transport of organic matter offshore, and diel vertical migration of zooplankton may also increase biological productivity (Brodeur 2001). In the Bering Sea, Pacific Ocean perch (*Sebastes alutus*) have an affinity for sea whip habitat associated with Probilof Canyon (Brodeur 2001), short-tailed albatross (*Phoebastria albatrus*) frequently forage along shelf edges and at marine canyons (Piatt et al. 2006), egg deposition by the Alaska skate (*Bathyraja parmifera*) Aleutian skate (*B. aleutica*) and Bering skate (*B. interrupta*) was high in areas near marine canyons for (Hoff 2010), and corals and sponges provide vertical relief in an area of otherwise low relief substrate in Zhemchung and Probilof canyon (Miller et al. 2012). These studies suggest potential associations between the structural complexity of canyons and the biological use and productivity of these habitats.

The development of geographic information systems (GIS) and related tools allow for more efficient spatial analysis and readily interpretable data visualization that may be valuable in the policy and management context of place-based frameworks. Furthermore, the application of remote sensing and remotely operated vehicle technology to the marine environment allows resource managers to inventory and map resources, quantify environmental characteristics, describe the flow of energy and matter and evaluate changes in ecosystem dynamics in new ways (Quattrochi and Pelletier 1991). Using remote sensing to model seafloor geomorphology provides an avenue to model seafloor terrain and explore potential relationships between habitat types and species assemblages that can be used to improve the understanding of a region and how processes are affected by seafloor geomorphology (Wilson et al. 2007). For example, steeply sloping areas can alter current flow, limit fishing gear use and influence community composition (Wilson et al. 2007).

Spatial statistical analysis is concerned with both the location and attributes of data (Wong and Lee 2005). It considers where phenomena occur in space and the spatial dependence and spatial heterogeneity among phenomena (Anselin 1993). Spatial analysis considers interactions between observations in space and distances between observations in space (Anselin 1993). It is used in diverse fields of inquiry to identify regions with extreme values and to explore the processes that may have led to those values and configurations of values (Ord and Getis 2001), as well as the ability to understand associations between observations based on distance (Legendre and Fortin 1989).

An underlying premise of spatial analysis is the concept of spatial autocorrelation. Spatial autocorrelation, the interdependence of values over space, is a common attribute among most ecological data (Legendre and Fortin 1989). Measuring the degree of spatial autocorrelation requires specifying a neighborhood or distance measure that locates *n* points in space (Ord and Getis 1995). Distance can be a relative position in space, such as a spatial arrangement, or an absolute position in space, such as Euclidean distance (Fortin and Dale 2005). Spatial autocorrelation will not be identical for all distances; a location that exhibits autocorrelation at one distance may not exhibit it at another distance (Legendre and Fortin 1989). Spatial scale is an important consideration for any analysis because the distance threshold used, or neighborhood, delineates the geographic scope of influence under investigation (Tobler 1979). Different neighborhood definitions will lead to different statistical values (Unwin and Unwin 1998). In ecological data, it is common to find positive spatial autocorrelation at short distances, with the possibility that negative spatial autocorrelation indicates too large a sampling interval for a given patch or ecological avoidance (Legendre and Fortin 1989). Spatial autocorrelation that is positive at a short distance and negative at a long distance indicates an ecological gradient, while positive autocorrelation at both short and long distances indicates an aggregation (Legendre and Fortin 1989).

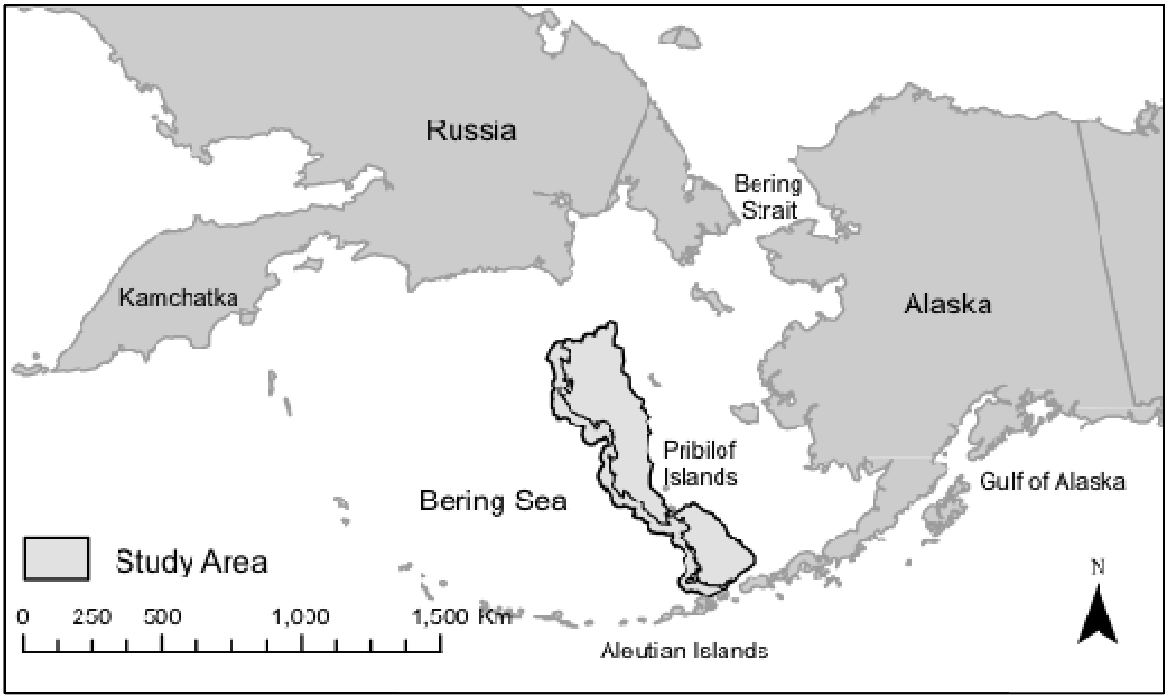
The use of local statistics facilitates investigation into sub-regional variation and acknowledges the likelihood that different processes are operating at different spatial and temporal scales within a study area (Fortin and Dale 2005). Global statistics used over large areas with large data sets can fail to detect fine-scale pattern, while local statistics compare each data point to its neighbors. A classic example from Ord and Getis (1992) considered Sudden Infant Death Syndrome mortality rates in North Carolina counties from 1979-1984. Global statistics did not detect spatial patterns in the data, but local statistics detected clustering of cases in a few southern counties. It is important to use global and local statistical analysis in combination to investigate spatial dependency and consider local statistical values in light of global values (Ord and Getis 2001). A local indicator of spatial autocorrelation (LISA) decomposes global statistics into parts, investigating whether a global pattern is representative of the average pattern of local associates (Anselin 1995). When a pattern is stable throughout the study area, there is little variation from the mean, but when there are significant deviations in values, these locations contribute a greater share towards the global statistic (Anselin 1995). Results of the local G_i^* statistic should be interpreted in the context of whether global autocorrelation is present (Ord and Getis 2001). The likelihood of Type I error in analyzing local statistical values can be increased when local results are interpreted in the absence of global statistical results since locations that appear as local 'hot spots' in G_i^* results may be located in areas with generally high values. Local statistics can be used to understand local pattern in the absence of global spatial autocorrelation and to explore cases where local patterns are an aberration from the global pattern (Ord and Getis 1995 and Anselin 1995).

Exploratory spatial data analysis can be used to determine and describe spatial structure in data in order to generate insights in spatial associations (Anselin 1993; Wilhelm and Steck 1998). These approaches allow researchers to visualize and describe geographic distributions, uncover patterns of spatial association, measure spatial heterogeneity and spatial instability, and identify outliers at both global and local levels (Anselin 1993; Wilhelm and Steck 1998). Global statistics provide a summary or average value for an entire area, while local statistics provide a unique value for each location.

Contemporary marine management is shifting towards place-based frameworks and tools; this approach has been incorporated into NPFMC management actions through an EBM approach to fisheries management (Witherell et al. 2000; Witherell and Woodby 2005). According to Belgrano et al. (2006), space constitutes and important variable in the Bering Sea system and exogenous and endogenous processes leading to ecological variation should be analyzed with consideration of spatial autocorrelation and multivariate methods. Spatial statistics and pattern analysis have the potential to inform place-based management frameworks, increase data integration, and improve data visualization. In this region, the continental shelf-slope break forms a conspicuous spatial feature. I used a hierarchical study design and spatial pattern analysis to integrate biological and structural information. I used groundfish distribution and abundance as a biological attribute and geomorphological heterogeneity of the outer continental margin as a structural attribute. I hypothesized that the structural complexity of the shelf-slope break would be statistically associated with spatial attributes of groundfish species. This approach provides a method for bounding space in a structurally complex marine environment and explores whether the geomorphological divisions imposed are meaningful in understanding groundfish distribution and abundance.

MATERIALS AND METHODS

Study area The Bering Sea is a semi-enclosed subarctic sea connecting the Pacific and Arctic Oceans. It is bounded by Russia to the west, Alaska to the east, the Aleutian Islands to the south and narrowly connected to the Arctic Ocean by the Bering Strait. The Beringian Continental Margin, extending from the Aleutian Islands to the Siberian Margin, bisects the sea into roughly two equal plains, a shallow continental shelf and deep sea basin. This region has a high degree of spatial heterogeneity, with seven marine canyons incising the shelf (Carlson and Karl 1984; Carlson and Karl 1988; Johnson et al. 2004). The study area of 218,068 km^2 includes the outer shelf and upper slope of the Eastern Bering Sea continental margin (Figure 1).



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Data Sources ETOPO1 was used for bathymetry and derivatives. ETOPO1 is a one-arc-second model of global relief developed by NOAA using land topography and ocean bathymetry (Amante and Eakins 2009). Although higher resolution bathymetry is available for portions of the study area, ETOPO1 has uniform 1.5 km cell resolution throughout the study area.

I utilized fisheries-independent direct *in situ* trawl survey data for groundfish distribution and abundance data. The groundfish data were taken from the 2002, 2004, 2008 and 2010 Eastern and Northern Bering Sea Continental Shelf Bottom Trawl Surveys of Groundfish and Invertebrate Fauna and Eastern Bering Sea Upper Continental Slope Surveys of Groundfish and Invertebrate Resources conducted by the Alaska Fisheries Science Center (AFSC). The Resource Assessment and Conservation Engineering (RACE) Division of the AFSC conducted both surveys between June and August each year. The shelf survey utilized a stratified systematic grid sampling approach in which the sampling grid consisted of fixed sampling stations at the center of each 37 X 37 km (20 X 20 nautical mile) grid square. Sampling density of the shelf survey ranged from one station per 775 km^2 to one station per 1,496 km^2 with a mean sampling density of one station per 1,311 km^2. The slope survey sampling grid consisted of random sampling within predefined geographic subareas based on bathymetric type and landscape features in an effort to represent habitat types (Hoff and Britt 2011). Sampling density for the slope survey ranged from one station per 112.39 km^2 to one station per 368.96 km^2 with a mean sampling density for the EBSS of one station per 204 km^2. Three chartered stern trawlers (43.5-m F/V Alaska Knight, 40-m F/V Aldebaran, and 38-m F/V Vesteraalen) conducted trawls for 30-minute durations at standard tow speeds of 3 knots for the EBS (Lauth 2011). One charted stern trawler (38-m F/V Vesteraalen) conducted trawls for 30-minute durations at standard tow speeds of 2.5 knots for the EBSS (Hoff and Britt 2011). Both surveys were conducted with eastern otter trawl gear with 25.3 m headropes and 34.1 m footropes (Hoff and Britt 2011; Lauth 2011). Species were recorded as catch per unit effort (CPUE) number by dividing the number of species caught per hectare swept. Species were also recorded as CPUE weight (kg) by dividing the catch weighs for each species by the hectare swept (Hoff and Britt

2011; Lauth 2011). For additional details regarding survey methods and data processing, refer to Lauth (2011) and Hoff and Britt (2011).

Table 1. Total stations by year.

	2002	*2004*	*2008*	*2010*
Total Number of Stations	248	340	310	310
Shelf Stations	135	171	154	163
Slope Stations	113	169	156	147
Northern Stations	122	148	146	147
Southern Stations	126	192	164	163

Because this study focuses on the outer continental shelf and slope area, the shelf survey data were partitioned based on depth. Trawl data from 100 m and greater from the EBS survey stations and trawl data from all EBSS survey stations were included in the analysis (Table 1).

All invertebrates as well as eggs, egg cases, shells and unidentified species were removed from the survey data. To assess spatial pattern among species and determine whether patterns of groundfish were driven by the most abundant species, the four most abundant species by CPUE flathead sole (*Hippoglossoides elassodon*), giant grenadier (*Albatrossia pectoralis*), Pacific Ocean perch (*Sebastes alutus*) and walleye pollock (*Theragra chalcogramma*) were analyzed individually. Within the Bering Sea Aleutian Island fishery, flathead sole, Pacific Ocean perch, and walleye pollock are classified as target species and giant grenadier as non-specified. Species categorized as target species are those with commercial value and non-specified species are those with no economic value and for which records are not maintained.

Methods ***Calculation of derivatives:*** I partitioned the study area into a shelf zone and slope zone by calculating the first and second order derivative of bathymetry to represent the slope and aspects and their local rates of change.

Definition of study area, geomorphic zones, and facets: The spatial extent of the study area was established by the international dateline to the north and the Alaska coast to the south with a combination of a 25 km spatial buffer around the point observations of the groundfish survey, the 100 m isobaths, and the digitized continuous line representing the toe edge of the slope. The slope-shelf break was established as a digitized line of maximum slope dividing the study area into the geomorphic shelf-zone and slope-zone. These geomorphic zones were further defined into facets based on slope and aspect morphology and adjacency of facets along the shelf. Facet initiation points identified the point of slope-shelf incision using a minimum mapping unit length of 100 km along the slope-shelf break. In the slope zone, facet boundaries were digitized following connected regions of maximum change in aspect. Given the very low structural complexity of the shelf geomorphic zone, facet boundaries in this zone were oriented orthogonally from the point of initiation at the slope-shelf break and continued to the intersection of the 200 km shelf-slope break line buffer. In this way each facet was recognized as an individual geomorphic unit within the study area extent. Polygon vector fields were added to the attribute tables of each facet designating the polygons as either slope or shelf geomorphic zones and each geomorphic facet was individually labeled north to south as F_{01}-F_{08} for slope facets and F_{11}-F_{18} for shelf facets (Figure 2). Subsequent spatial analysis was used to compare response variables across geomorphic zones and facets and between northern and southern portions of the extent. The groundfish data sets were spatially intersected with the polygon attributes to aid in interpreting results.

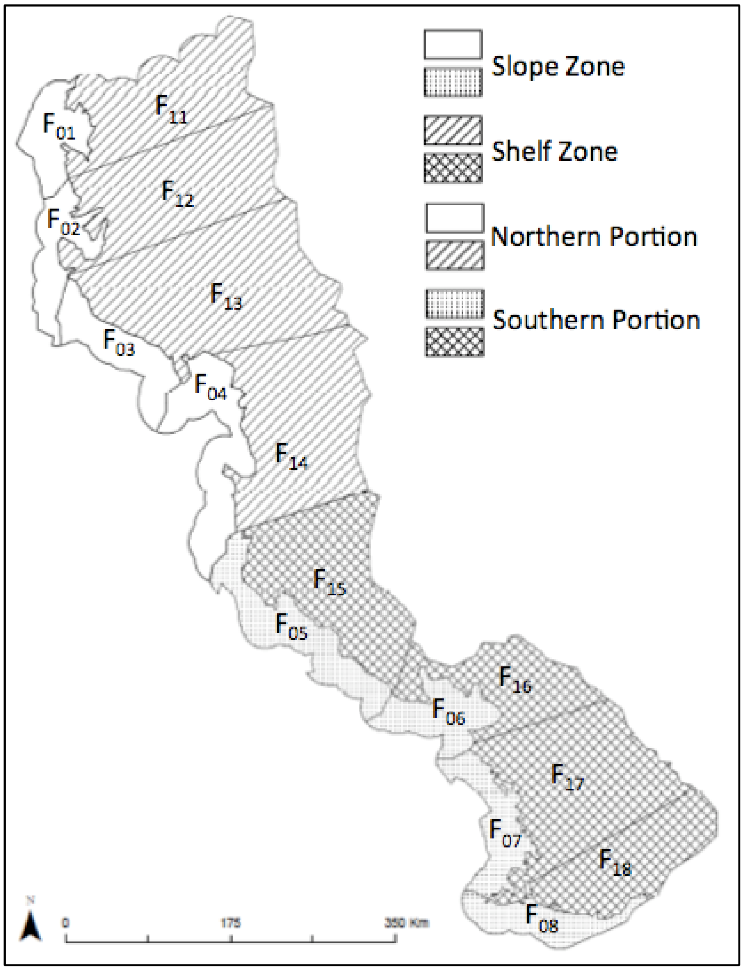


Figure 2. Spatial scales captured within the study area highlighted by pattern type and facet number.

Structural pattern metrics: Quantitative measures of shape complexity and surface roughness (rugosity) were calculated for each facet. These two terms represent the relative spatial complexity between facets in the study area in the horizontal and vertical dimensions. Shape index is a measure of shape complexity where the patch shape is compared to a standard shape (square). This metric is calculated as (McGarigal et al. 2002):

$$shape\ index = \frac{0.25\ P_{ij}}{\sqrt{a_{ij}}}$$

Where 0.25 serves as a constant to adjust for the standard shape, P_{ij} is the perimeter of patch *ij* and a_{ij} is the area of patch *ij*. When shape index equals one, the shape is a square; the value increases as the patch becomes more irregular. Rugosity is a measure of surface roughness and was calculated by dividing the surface area by planimetric area (Jenness 2011). Shape index and rugosity were calculated for each geomorphological facet in the study area.

Spatial trend: The geographic mean center is the point representing the geometric center of a point distribution. When these spatial observation points are weighted by an attribute value such as count, the shift in direction and distance between the mean center and the weighted mean center is a measure of spatial trend in the observed data. In this study, shifts in the weighted mean center indicate shifts in groundfish species abundance (measured in CPUE number and weight) and species richness vary in magnitude and direction over time in relation to the geographic mean center.

Global statistics: The Moran's *I* and Getis-Ord general *G* are used in this analysis to investigate the variation in the autocorrelation of the measured variables among the different units of analysis. Moran's *I* is a measure of correlation based on the degree of covariance among values where the general *G* is based on proportional distribution of values (Moran 1950; Getis and Ord 1992). Both global autocorrelation statistics are weak in detecting variations in spatial dependence and are instead focused on characterization of similarity of measured values as a function of distance or adjacency. One advantage of general *G* over Moran's *I* is its ability to distinguish between patterns of high values and patterns of low values. Moran's *I* is only able to distinguish the presence of spatial pattern. Another frequently used measure of global spatial autocorrelation is Geary's *C*, but Moran's *I* is often preferred because the results are easily interpretable (scaled from -1 to 1) and more closely resembles Pearson's Correlation Coefficient (Legendre and Fortin 1989). In addition, because Geary's *C* is calculated directly from attribute values, its variance is affected more greatly by the sample distribution than that of Moran's *I*, which is calculated from differences in reference to the mean (Cliff and Ord 1981). Global Moran's *I* is calculated as according to Wong and Lee (2005):

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}) \sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Where *n* is the number of observations; w_{ij} is a spatial weights matrix indexing location *i* in proximity to location j; $\bar{x}$ is the mean of the variable over all locations; x_i and x_j are the variable's value at two particular locations. With the exception of the weights matrix (w_{ij}) all terms are calculated directly from attributes of the data.

Moran's *I* detects spatial pattern in data by measuring whether high values are proximate to high values and low values proximate to low values for an attribute given the weight matrix used. When high values occur in neighborhoods of high values or low values occur in neighborhoods of low values, Moran's *I* is positive. When high values occur in neighborhoods of low values or low values occur in neighborhoods of high values, Moran's *I* is negative. The Getis-Ord general *G* statistic is calculated as (Getis and Ord 1992):

$$G(d) = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(d) x_i x_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j} \text{ , } j \text{ not equal to } i$$

Where *n* is the number of observations; w_{ij} is a spatial weights matrix indexing location *i* in proximity to location j; *d* is distance; x_i and x_j are the variable's value at two particular locations.

General *G* detects the spatial concentration of values in data by measuring, for a specific attribute, whether high values are clustered around other high values and whether low values are clustered around other low values. In interpreting general *G*, both positive and negative z-scores indicate spatial autocorrelation, but a significant positive z-score indicates high values clustered near high values and a significant negative z-score indicates low values clustered near low values. Thus general *G* indicates both whether there is spatial structure present in data and the type of structure, unlike Moran's *I* that can indicate only whether there is spatial structure.

Local statistics: Local statistics acknowledge that processes can vary within a geographic region and provide insights on the presence of localized patterns that might not be detected using global statistics. Rather than providing a global average value, these statistics provide a measure of autocorrelation for each location. Results of local statistics can be mapped to aid in interpretation because they produce individual values for each location. Similar to global measures of spatial pattern, each local statistic measures a different aspect of spatial autocorrelation so it is recommended to use more than one statistic (Wilhelm and Steck 1998).

I used local Moran's *I* and G_i^* statistics in this analysis. Local Moran's *I* decomposes global Moran's *I* by measuring the degree to which locations in a specified neighborhood have similar attribute values; the sum of these values is proportional to the measure of global spatial autocorrelation (Anselin 1995). Following Anselin (1995), the local Moran's *I* statistic is calculated as:

$$I_i = z_i \sum_j w_{ij} z_j$$

Where z_i and z_j are locations that deviate from the mean; w_{ij} is a spatial weights matrix; and the summation over *j* ensures only neighboring values are included in the calculation.

Local Moran's *I* measures the degree of similarity of attribute values among neighboring locations. Resulting values that are large and positive indicate concentration of high values or low values (high values in neighborhoods of high values or low values in neighborhoods of low values). Values that are large and negative indicate heterogeneity (high values in neighborhoods of low values or low values in neighborhoods of high values). Large positive values can serve as outliers or leverage points, locations that exert a strong influence on the global value (Wilhelm and Steck 1998). The G_i^* statistic (Ord and Getis 1995) is calculated as:

$$G_i^*(d) = \frac{\sum_j w_{ij}(d)x_j - W_i^*\bar{x}}{s\{[nS_{1i}^* - W_i^{*2}]/(n-1)\}^{1/2}} \text{, all } j$$

Where w_{ij} is a spatial weights matrix; W_i^* = $W_i + w_{ij}$; d is distance; $\bar{x}$ is the mean of the variable over all locations; *s* is the sample variance; S_{1i}^* = $S_{1i}^* = \sum_j w_{ij}^2$ (for all j). Because the G_i^* includes all j it includes values where $w_{ij} \neq 0$ unlike the general *G* statistic. In interpreting G_i^* a large positive z-score indicates the presence of high value clusters and a large negative z-score indicates the presence of low value clusters.

Determination of spatial relationship and distance: A 50,000 km distance threshold was used for calculation of neighborhood statistics based upon the results of the Ripley's *K* multi-distance spatial cluster analysis that summarizes spatial dependency over a range of distances. A zone of indifference was used for the spatial relationship, in which all features within the 50,000 km distance were included in the analysis of each target feature; beyond this threshold the degree of influence of the feature declines exponentially with distance.

Data analysis All data analysis was conducted with ArcGIS Version 10.0 (Environmental Systems Research Institute, ESRI).

RESULTS

Structural pattern metrics Measures of structural complexity indicated clear differences between shelf and slope geomorphological zones (Figure 3), but differences between the northern and southern portions of the study area were not detected. Differences between individual facets varied based on the metric used. Among the shelf facets, complexity was lowest in F_{13} and highest in F_{16} based on the shape index metric (Figure 3). Of the slope facets, complexity was lowest in F_3 and highest in F_2 and F_7. The incised facets (F_1, F_2, F_4 and F_6) did not appear to have greater complexity than those that were not incised. Among facets on the shelf, rugosity was lowest in F_{16} and F_{17}, and highest in F_{14}. Among facets on the slope, rugosity was lowest in F_7 and F_8, and highest in F_5. The incised shelf facets did not exhibit the greatest complexity as measured in rugosity. Shelf and slope facets did not differ with respect to rugosity or complexity.

Neither of these methods seemed to detect differences between incised and non-incised slope facets.

Spatial trend Spatial trends in species abundance and richness were consistent over time (Figure 4). In all years, CPUE (measured as number and weight) trended northwest of the geometric mean center. The weight CPUE weighted mean center was the greatest distance from the geometric mean center in all years. Species richness trended a southeast direction in all years. The distance between the weight CPUE weighted mean center and the geometric mean center was greatest in 2004 and 2010, while distance between the species richness weighted mean center and the geometric mean center was greatest in 2002 and 2004. Although results indicated variations in the distance, or magnitude, between weighted attributes and between years, the directional trend of each weighted attribute was consistent over all years.

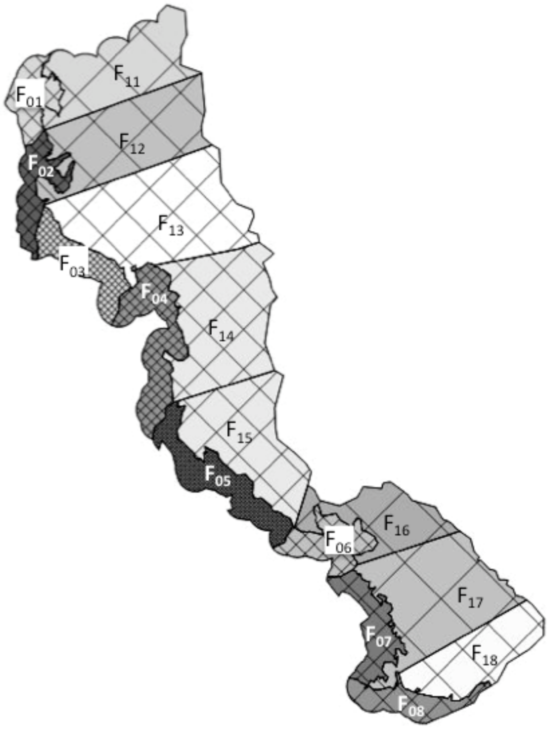


Figure 3. Facet complexity as quantified by shape complexity metrics. Shading lighter to darker indicates increasing complexity measured by the shape index metric. Crosshatching larger to smaller indicates increasing surface roughness measured by the rugosity metric.

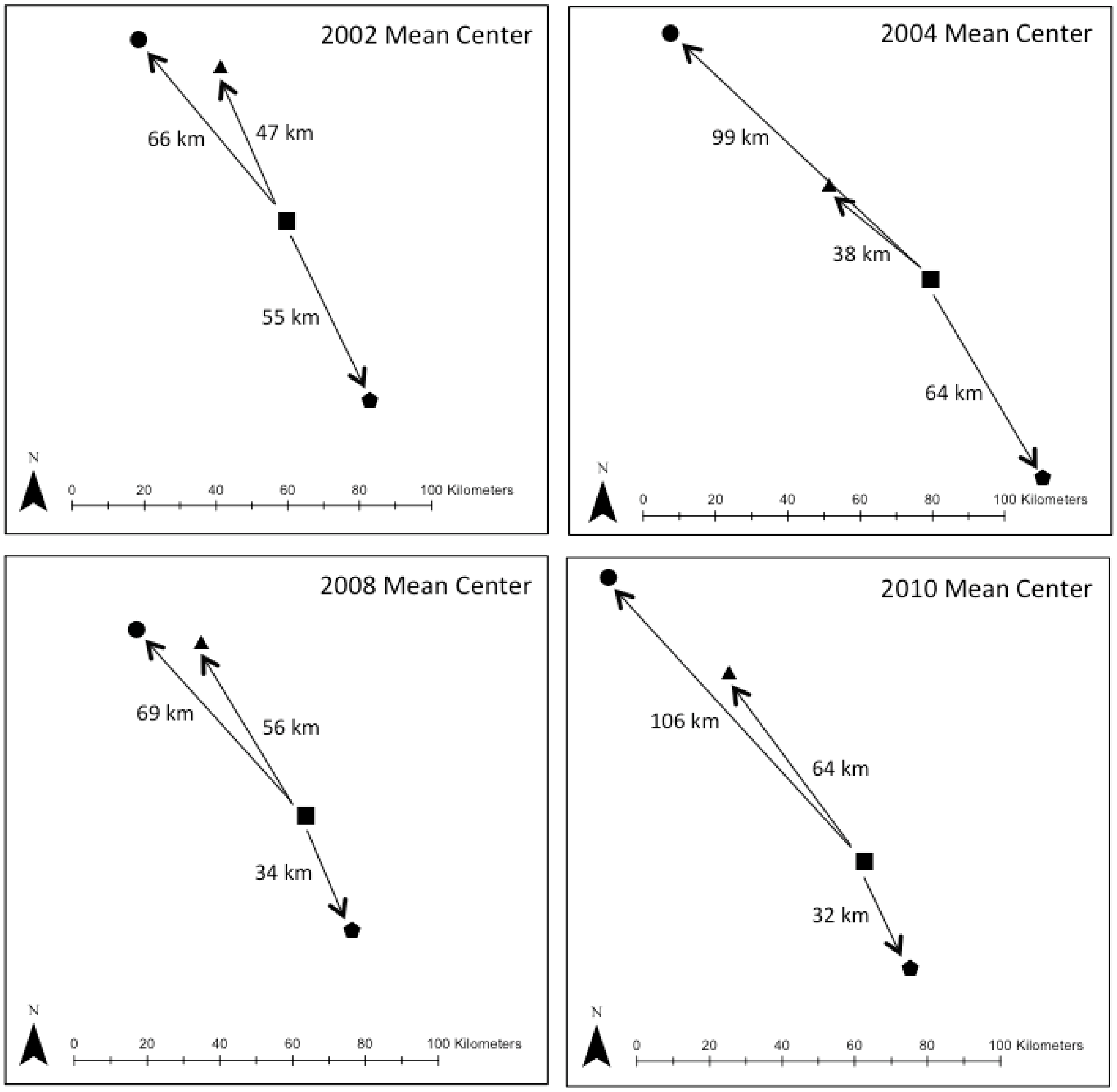
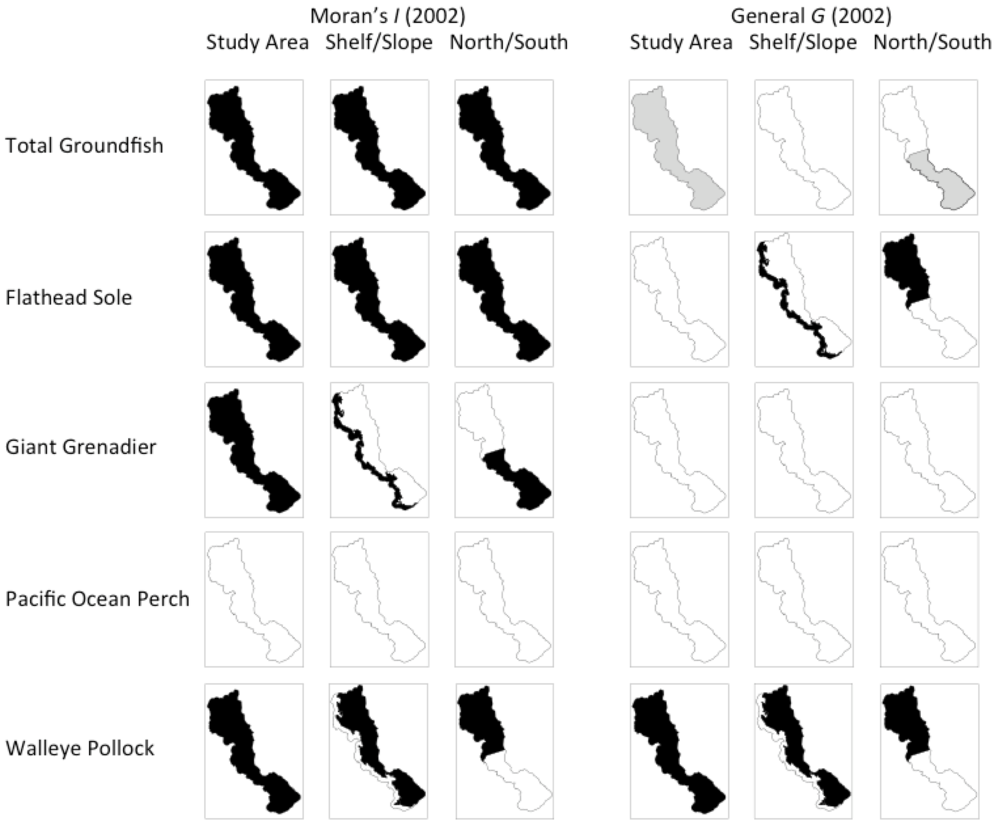


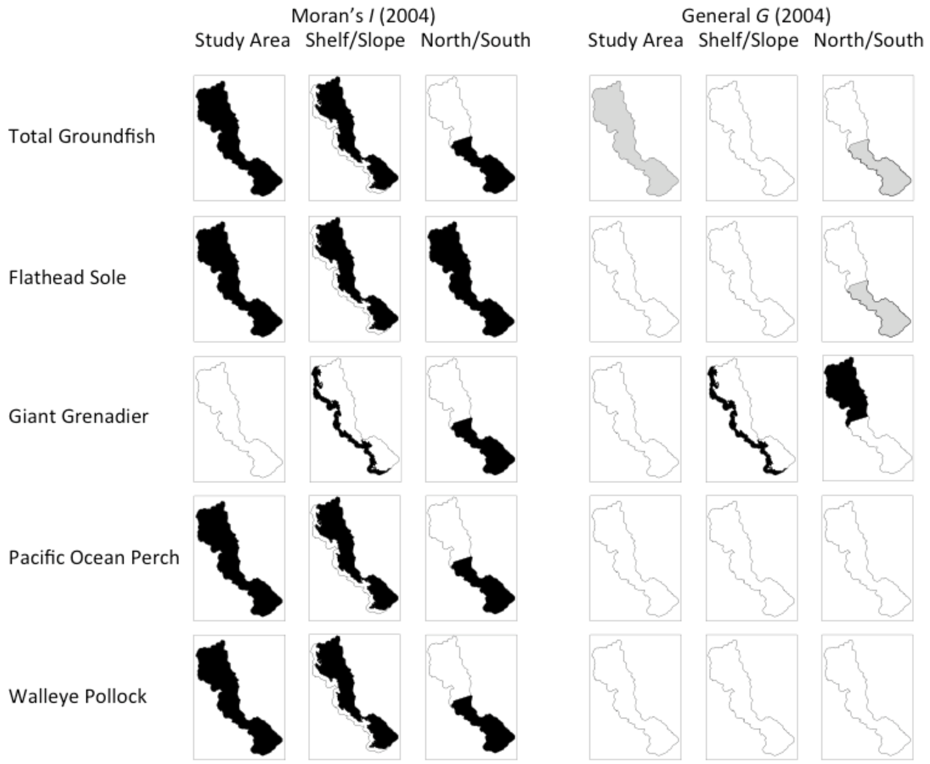
Figure 4. Geographic mean center (■) and weighted mean center for CPUE number (▲), CPUE weight (●), and groundfish species richness (⬟) for the study area by year.

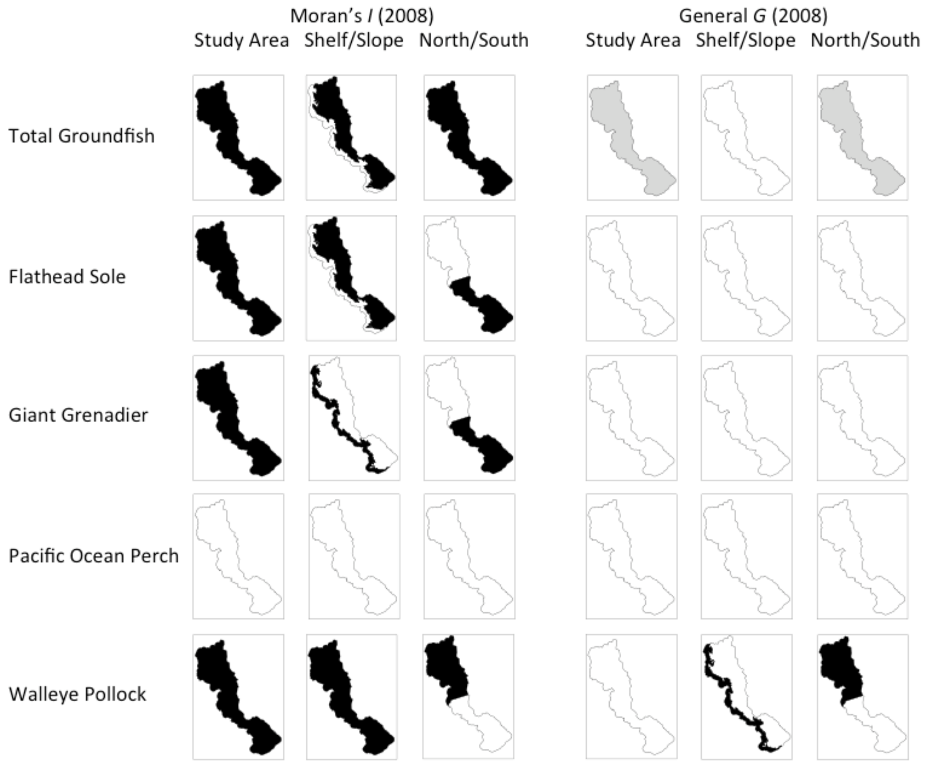
Global statistics. ***Moran's I:*** The Moran's *I* test indicated that groundfish were not dispersed and exhibited significant clustering (p-value < 0.05). Results of the Moran's *I* test indicated the occurrence of spatial autocorrelation at the scale of the study area in all years for total groundfish and individual species except Pacific Ocean perch at the study area level based on CPUE number (Figure 4 and Appendix Table 1). Total groundfish, flathead sole and walleye pollock CPUE were autocorrelated in the shelf zone in all years, while giant grenadier was autocorrelated in the slope zone in all years. Pacific Ocean perch exhibited the greatest variability in spatial autocorrelation. The pattern was not significantly different from random in 2000 and 2008, but in 2004 Pacific

Ocean perch were autocorrelated in the shelf zone and in 2010 in the slope zone. Moran's *I* results indicated variability in autocorrelation in the northern and southern portions between years and species.

General G: Results of the general *G* indicated less spatial autocorrelation than results of Moran's *I*. The general *G* indicated clustering of low and high values (Figure 5 and Appendix Table 2). Based on this spatial analysis, groundfish CPUE were clustered at the study area level and the southern portion in 2002, 2004 and 2008 and the northern portion in 2008. No spatial patterns were detected for groundfish CPUE in 2010. Flathead sole CPUE varied in clustering pattern based on year and area. Giant grenadier CPUE was rarely autocorrelated. Pacific Ocean perch CPUE were only autocorrelated in the slope zone in 2010. Walleye Pollock results varied from no spatial autocorrelation to high value clusters in CPUE.




Moran's *I* (2004)
Study Area
Shelf/Slope
North/South
General *G* (2004)
Study Area
Shelf/Slope
North/South
Total Groundfish
Flathead Sole
Giant Grenadier
Pacific Ocean Perch
Walleye Pollock


Moran's *I* (2008)
Study Area
Shelf/Slope
North/South
General *G* (2008)
Study Area
Shelf/Slope
North/South
Total Groundfish
Flathead Sole
Giant Grenadier
Pacific Ocean Perch
Walleye Pollock

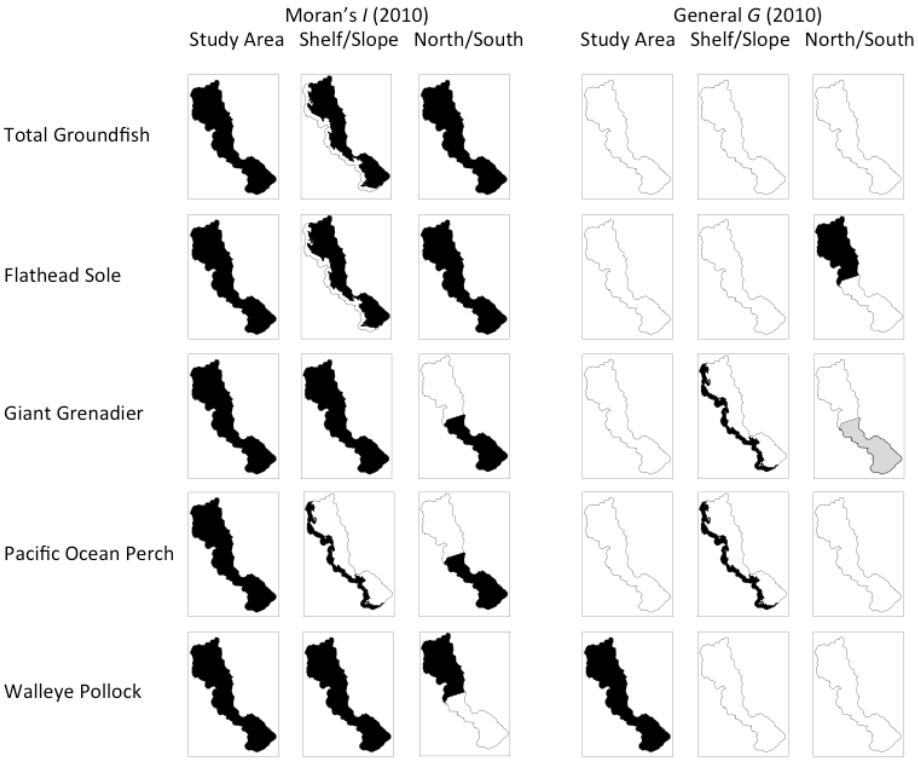
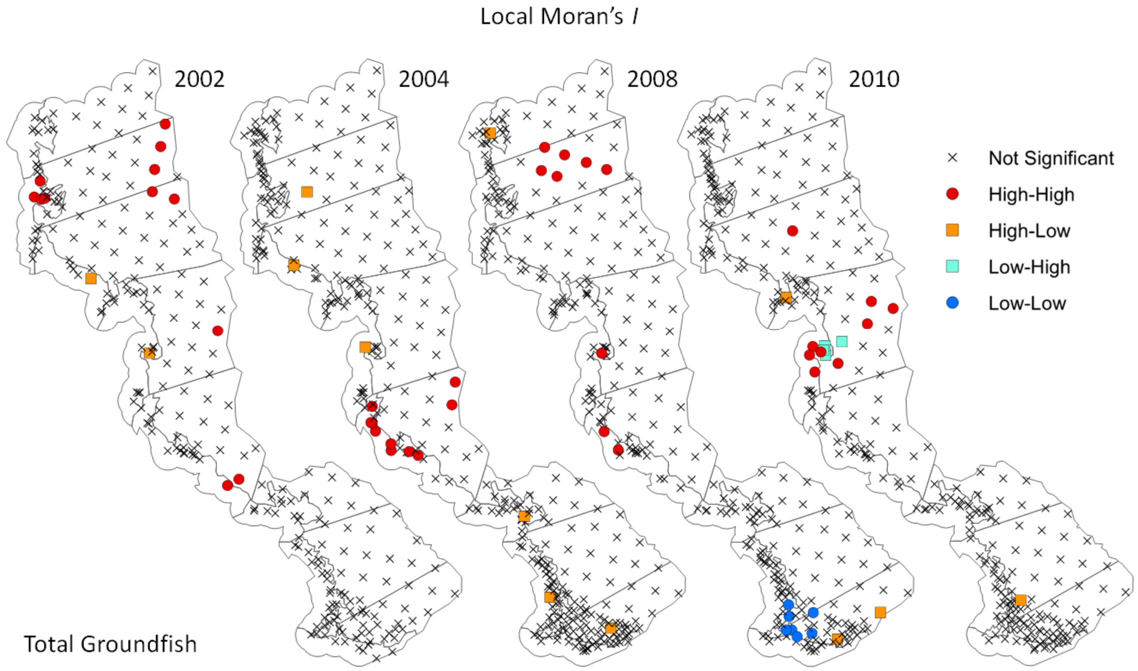
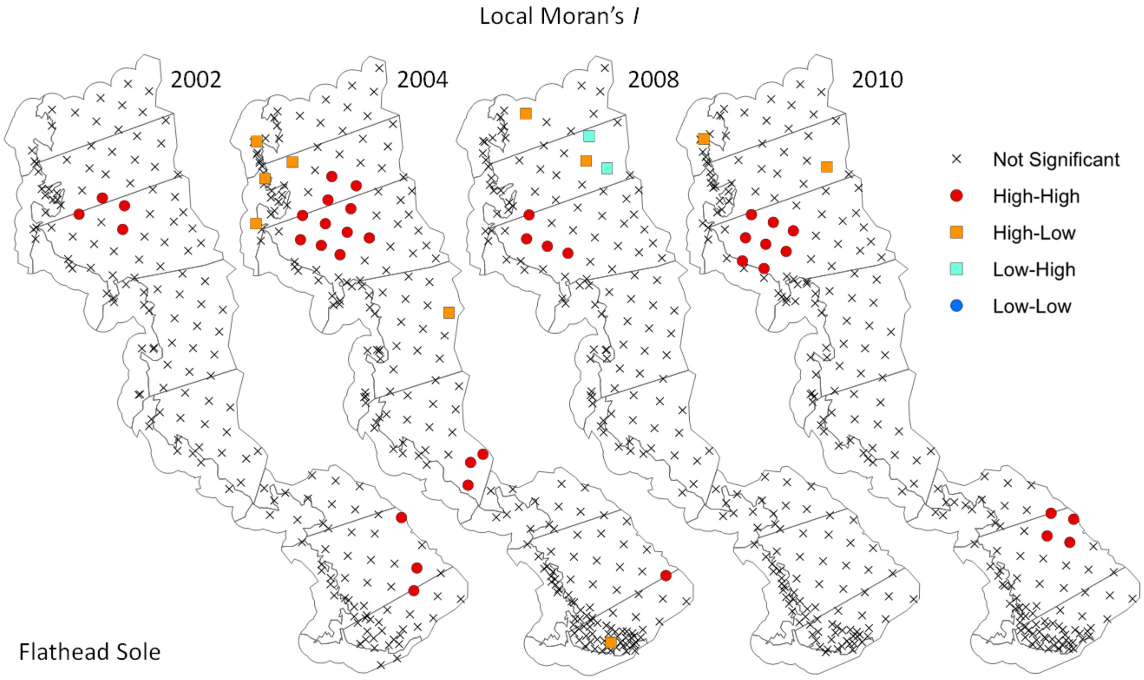


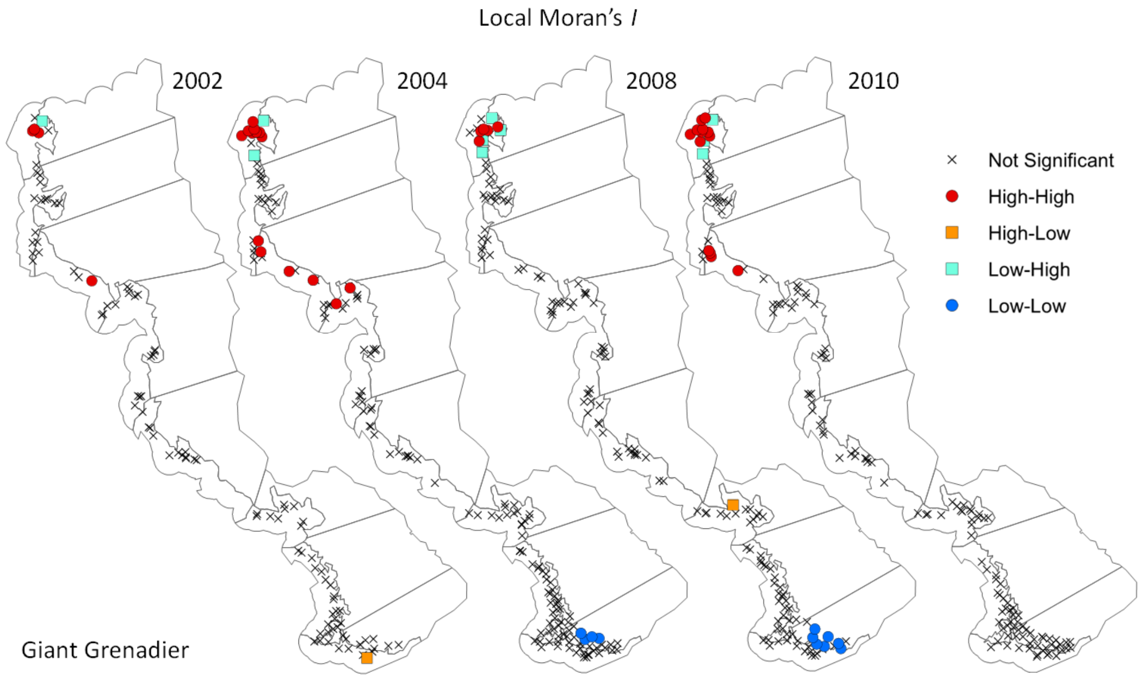
Figure 5. Global statistical results by total study area, slope and shelf zones and northern and southern portions. Black shading indicates significant spatial autocorrelation for Moran's *I* results, black shading indicates significant spatial clustering of high values for general *G* results and gray shading indicates significant spatial clustering of low values for general *G* results. In unshaded regions the distribution did not differ from random.

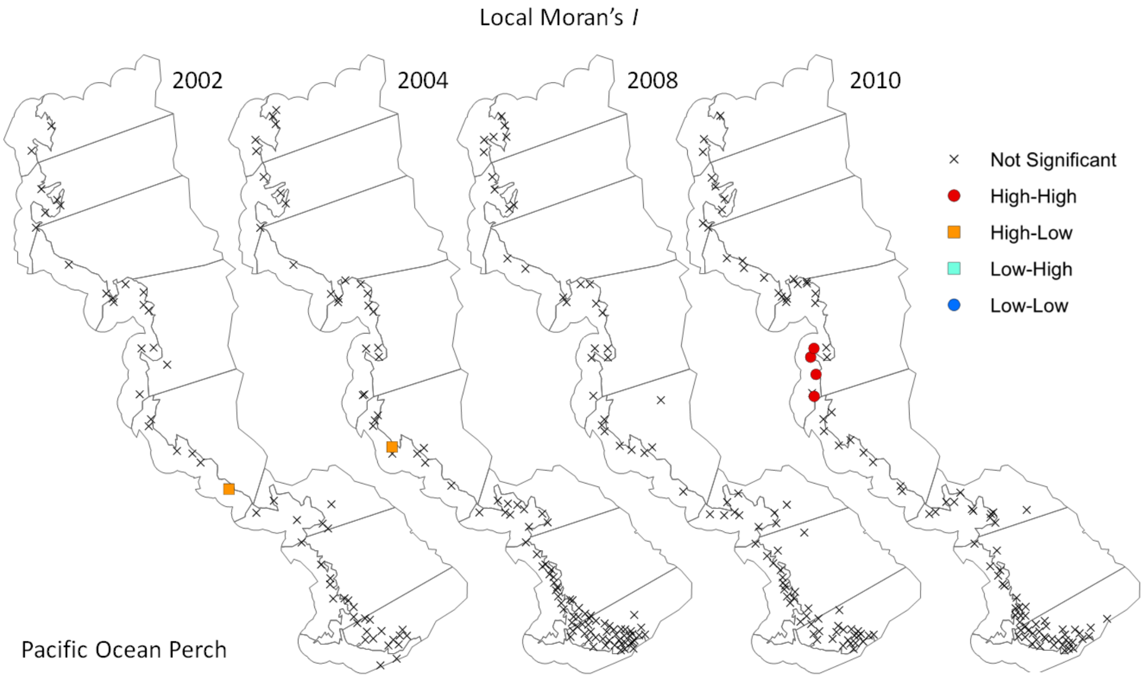
Local statistics ***Local Moran's I:*** Local Moran's *I* indicated a variety of clusters and outliers in CPUE between years and species (Figure 6). High value outliers and low value outliers were detected among total groundfish CPUE. Low value outliers were detected for flathead sole and giant grenadier and high value outliers were detected for all individual species. High value clusters were detected among total groundfish CPUE and all individual species, but low value clusters were detected only for total groundfish and giant grenadier. Outliers were congregated along the shelf-slope break for total groundfish CPUE and varied among shelf and slope zones by year. Flathead sole results indicated high value clusters and outliers in F_{12} and F_{13} in all years, with low value outliers present in F_{12} in 2008. Giant grenadier results indicated both high value clusters and high value outliers in F_1 in all years. Pacific Ocean perch had the fewest occurrences of clusters and outliers and they were consistently located in F_4 or F_5 of the slope zone.

Walleye Pollock high value clusters varied from year to year among F_{11}-F_{16} of the shelf zone.






Local Moran's *I*
2002
2004
2008
2010
× Not Significant
● High-High
■ High-Low
■ Low-High
● Low-Low
Giant Grenadier


Local Moran's *I*
2002
2004
2008
2010
× Not Significant
● High-High
■ High-Low
■ Low-High
● Low-Low
Pacific Ocean Perch

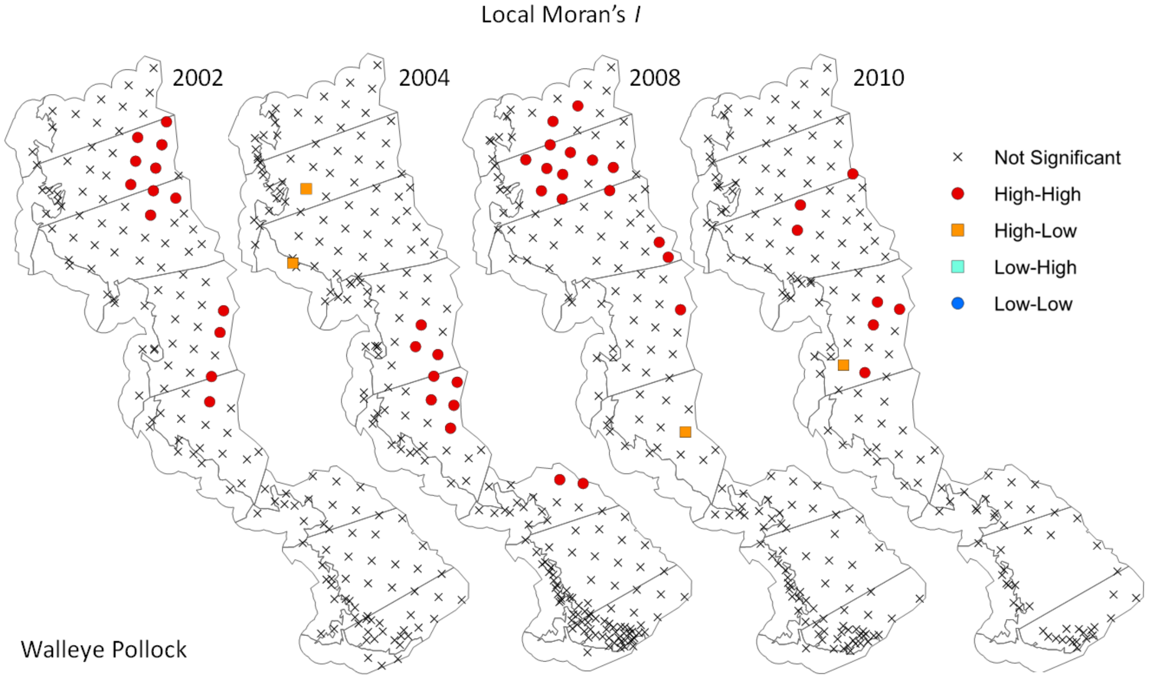
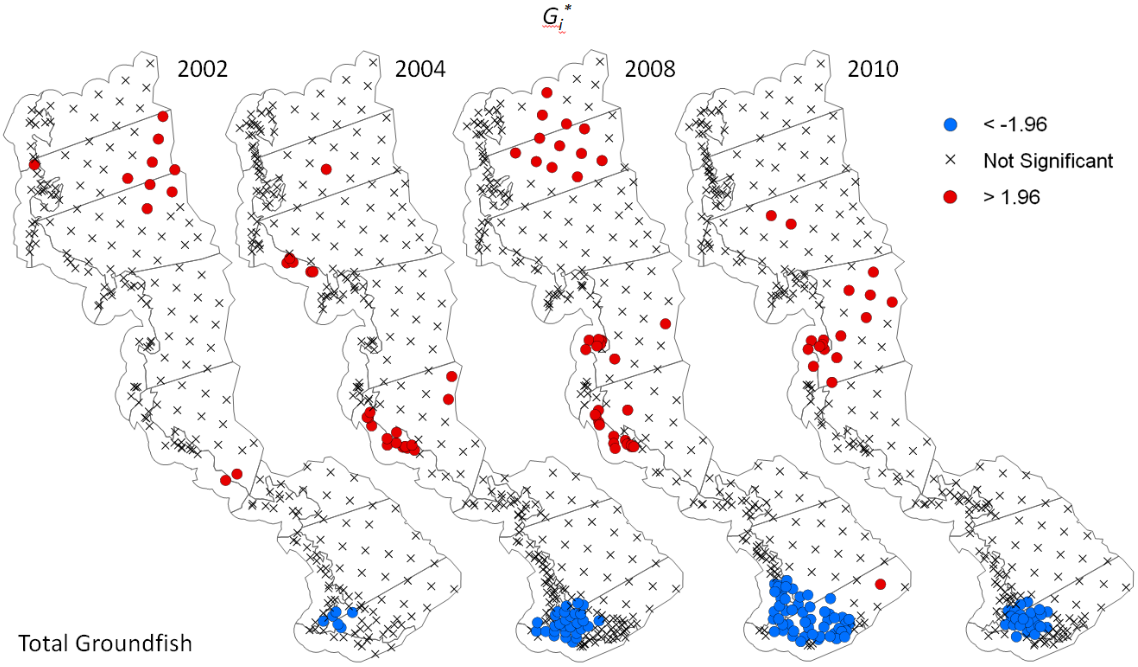
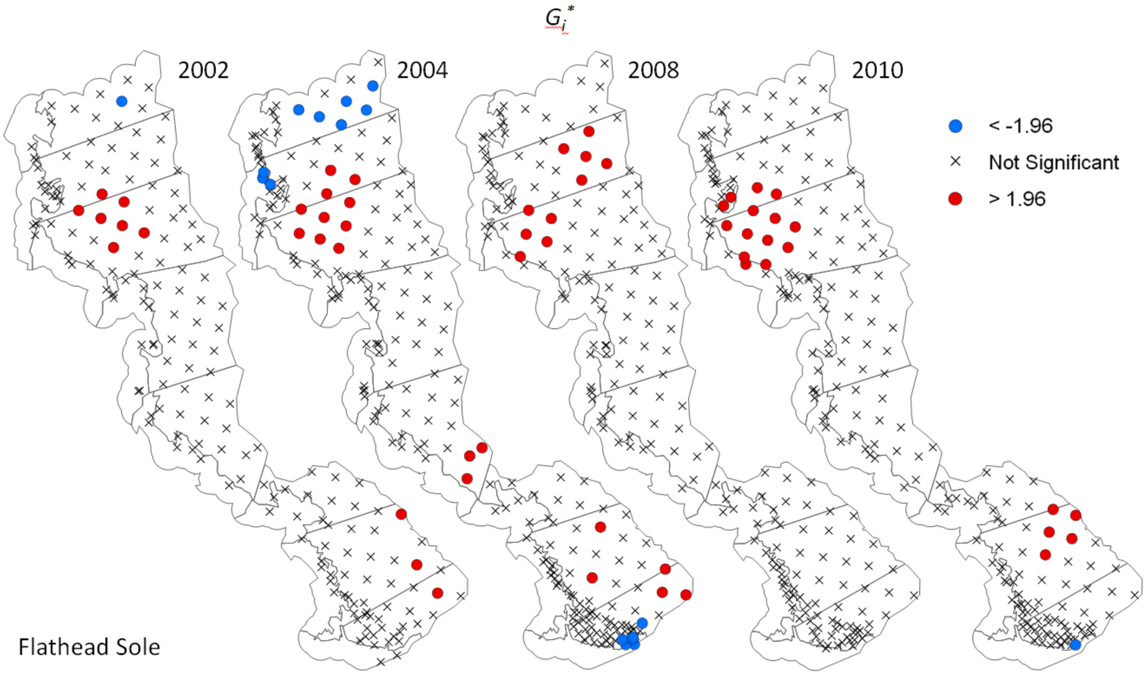
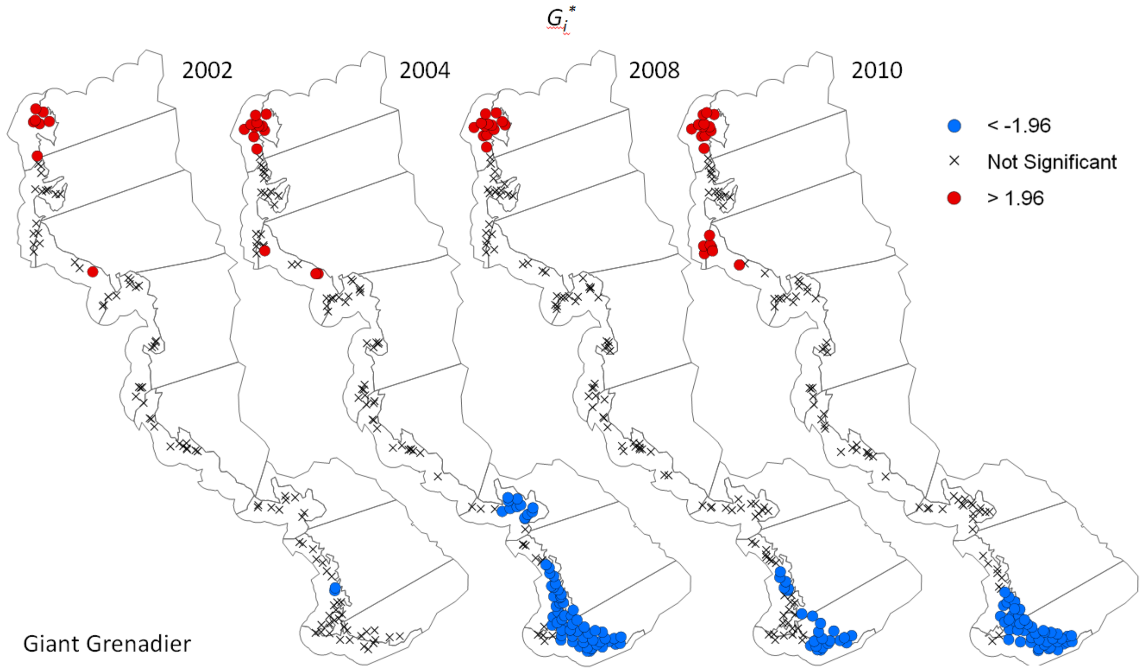


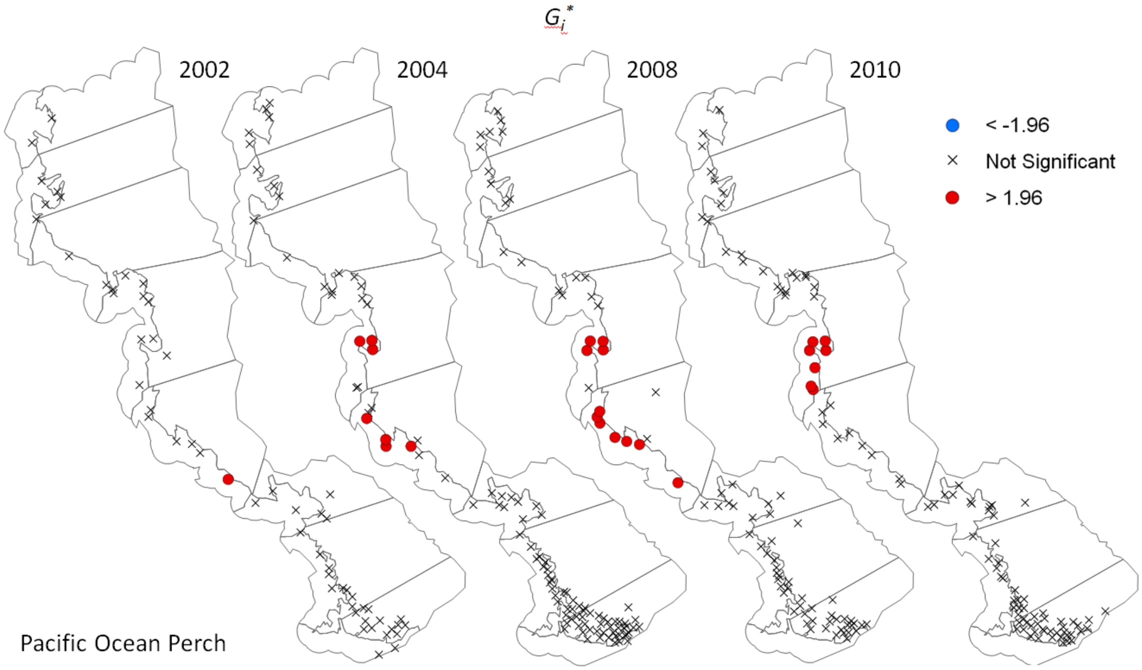
Figure 6. Local Moran's *I* results by species and year. Circles indicate clustering, while squares indicate outliers of CPUE number.

G_i^*: The G_i^* results indicated a wide range of high and low clustering among years and species (Figure 7). Among total groundfish CPUE G_i^* results indicated low value clustering in the southern portion of the study area in all years with varying magnitude. High value clusters of total groundfish CPUE were variable, ranging from the shelf to the slope zone and from the northern to the southern portion of the study area. The location of flathead sole CPUE clusters also varied greatly by year with high value clusters detected in the northern and southern portions of the study area and one low value cluster detected in F_{11} in 2002, both high and low value clusters detected in the uppermost and lowermost facets in 2004, only high value clusters detected in the northern portion in 2008, and high value clusters detected in the northern and southern portions and one low value cluster in F_{18} in 2010. Giant grenadier results indicated clustering of high values in F_1 in all years and frequent low value clustering in F_7 and F_8. Pacific Ocean perch were present along the entire shelf-slope line but had the least spatial autocorrelation. Pacific Ocean perch CPUE high value clusters were detected in F_4 and F_5. No low value clusters were detected. Walleye pollock CPUE results indicated clustering of high values throughout the northern portion of the shelf zone, with some high value clustering in F_{15} and F_{16} and one station in F_{18}. Low value clusters were detected in 2004 and 2008 and confined to the southern portion.






G_i^*
2002
2004
2008
2010
● < -1.96
× Not Significant
● > 1.96
Giant Grenadier


G_i^*
2002
2004
2008
2010
● < -1.96
× Not Significant
● > 1.96
Pacific Ocean Perch

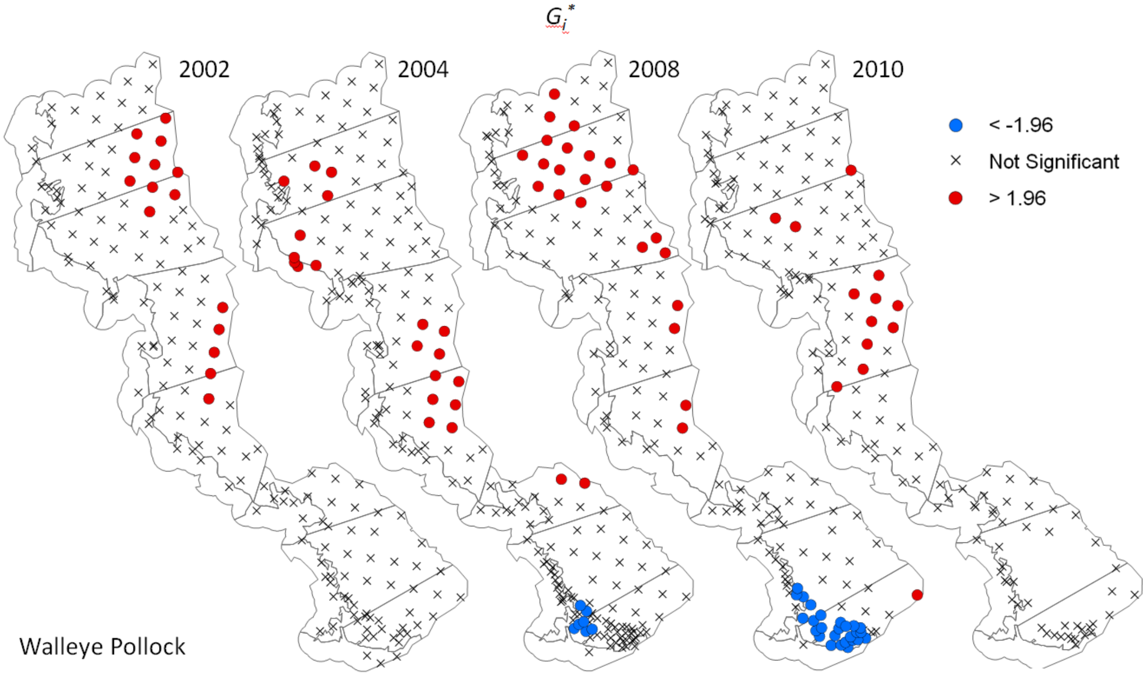


Figure 7. G_i^* results by species and year. Blue circles indicate clustering of low values, while red circles indicate clustering of high values of CPUE (number).

DISCUSSION

The results of this study demonstrate that spatial analysis of fisheries data can provide new insights into the distribution of species abundance (or variation in abundance with respect to space). Groundfish abundance on the outer continental margin of the Eastern Bering Sea varied over space and time, but some regions exhibit consistently high or low abundance. The results of global and local statistical analysis demonstrated that the structural complexity of the shelf-slope break is associated with spatial attributes of groundfish abundance.

A thin ribbon of higher abundance around the shelf-slope break is apparent in the results. In some years and with some species, this feature appears to move shelf-ward, while in other years and among other species it appears to move slope-ward. This observation is consistent with work by Springer et al. (1996) who termed this region of the Bering Sea the Green Belt. Those authors found that primary and secondary productivity along the Bering Sea shelf edge is enhanced compared with neighboring regions. They contended that shelf edge processes are critical to maintaining fish, mammal and avian populations. Spatial analysis can provide insights to ecological process since the presence of pattern indicates the presence of ecological process(es) that govern the exhibited pattern. Detecting these patterns and seeking to understand the processes that drive the pattern can provide information to managers on interactions of ecosystem components.

Evidence for high productivity along the outer continental margin has been detected elsewhere. Spatial variability is high on continental margins and this complexity impacts the flow of water, sediments, and nutrients from continental shelves to ocean basins (Springer et al. 1996; Rogers et al. 2003; Bianchelli et al. 2008). Although these systems play a meaningful role in ocean dynamics, they remain poorly understood but exposed to a high degree of human use due to fishing pressure and oil and natural gas extraction (Rogers et al. 2003). The application of remote sensing and spatial analysis tools will provide new insights into these regions. Remote sensing and spatial analysis are tools readily applied to inaccessible marine regions. Spatial analysis can be applied to current data acquisition to aid in reducing data collection costs and provide a new lens to view existing data sets. The insights gained from spatial analysis can contribute to marine resource management through refining our knowledge of ecosystems, improving data visualization and expanding data integration.

Boundary delineation poses a challenge to spatially-explicit forms of marine resource management (Sissenwine and Murawski 2004). Tools are needed to improve our understanding of these issues and provide guidance to managers and decision makers. The spatially-explicit visualizations produced by spatial statistics and pattern analysis can be beneficial in addressing these challenges. Spatial statistics and pattern analysis provide techniques to monitor species distribution and abundance over space and time. These tools can be used to incorporate spatially explicit information in stock assessments and food web modeling or can be integrated into multivariate analysis and spatial modeling. The use of geomorphology to delineate hierarchical boundaries in this study provided insights into how structural heterogeneity of the outer continental shelf of the Eastern Bering Sea relates to groundfish distribution and abundance.

The two measures of structural complexity used in this study, shape index and a surface area based rugosity measure, both failed to differentiate incised geomorphological facets from those that are not incised. The lack of differentiation using these methods could result from the techniques used to derive these metrics and cell size or scale of the data. For example, the rugosity metric considered only surface area; it did not consider aspect, or the direction of orientation, in calculating rugosity. In the case of the shape index, finer scale resolution of facet edges would lead to greater complexity. Other measures of complexity exist, such as a contour index (Yen et al. 2004) that measures the total range in depth over an area divided by the maximum depth of that area or a suite of tools in the Bathymetric Terrain Modeler (BTM) developed by NOAA Coastal Services Center and Oregon State University, but BTM is not currently compatible with versions of ArcGIS higher than Version 9.2. Exploring other measures of complexity, and at varying scales, may lead to different results. Managers are faced with the need to determine the appropriate scale of inquiry, which is not the same for all ecosystems or ecosystem components. Understanding what question is being asked and the appropriate scale for that question is a continuing challenge for marine resource managers.

Although the results do not allow inference with regard to differential distribution of marine resources and their association with incised slope facets or marine canyons, ongoing research on marine canyons in the Bering Sea and elsewhere (Brodeur et al. 2001; Hoff 2011; Miller et al. 2012) indicate that these regions could support enhanced productivity. Some evidence shows that canyons may also serve as barriers for along-slope processes because they create discontinuity along the shelf (Gage 2003; Rogers et al. 2003). Understanding these complex geomorphological features should be a goal of fisheries management and research. Finer scale resolution in bathymetric coverage and biological data collection within the outer continental margin of the Eastern Bering Sea may lead to a more nuanced understanding of interactions between seafloor geomorphology and features and biological attributes. These regions, as portions of the outer continental margin in general, are undergoing pressure from increased human use and disturbance, but we have limited knowledge of how vulnerable or resilient these regions are to human impacts (Levin and Dayton 2009). Fisheries are expanding onto upper continental slopes, but the impacts to deep sea fish, which are often long lived, slow growing and late maturing species, as well as to the benthic habitat are not well known (Levin and Dayton 2009). Outer continental margins tend to have patch-like structures of high vertical relief habitat among vast areas of sandy or silty habitat according to Levin and Dayton (2009) and recent research in the Bering Sea by Miller et al. (2012). Understanding the possible interplay between species, geomorphological structure and habitat types allows managers greater ability to delineate boundaries in place-based management approaches.

SUMMARY

Spatial statistics and pattern analysis are tools that can provide new insights and improve data visualization and integration. Fishery managers and policy makers can gain greater comprehension of marine resource abundance and distribution through this explicitly spatial approach. These tools can be used to better understand interactions within ecosystems and consider how fishing effort is distributed in the Eastern Bering Sea. Understanding spatial patterns in abundance and the underlying processes that create patterns can help to improve place-based marine management. The results of this study demonstrate the utility of spatial approaches in fisheries management and show how these approaches can advance our understanding of marine systems.

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APPENDIX

Table 1. Moran's *I* values by study area, shelf and slope zone and northern and southern portions by year.

Total Groundfish CPUE (number)	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*
Study Area	2002	0.10	**3.85**	2004	0.06	**3.83**	2008	0.09	**4.68**	2010	0.09	**5.37**
Shelf Zone	2002	0.17	**4.02**	2004	0.07	**2.85**	2008	0.22	**6.07**	2010	0.12	**4.49**
Slope Zone	2002	0.06	**1.76**	2004	0.04	1.91	2008	0.02	1.07	2010	0.03	1.62
Northern Portion	2002	0.09	**2.21**	2004	-0.05	-1.44	2008	0.06	**2.13**	2010	0.08	**2.87**
Southern Portion	2002	0.06	**2.46**	2004	0.11	**6.76**	2008	0.09	**4.08**	2010	0.07	**3.53**
Flathead Sole CPUE (number)	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*
Study Area	2002	0.14	**3.79**	2004	0.11	**4.47**	2008	0.06	**2.32**	2010	0.13	**5.18**
Shelf Zone	2002	0.12	**2.69**	2004	0.17	**5.89**	2008	0.07	**2.32**	2010	0.18	**5.81**
Slope Zone	2002	0.33	**3.37**	2004	-0.10	-1.30	2008	0.04	0.73	2010	-0.07	-0.84
Northern Portion	2002	0.16	**3.26**	2004	0.16	**3.39**	2008	0.01	0.40	2010	0.16	**3.75**
Southern Portion	2002	0.13	**2.73**	2004	0.12	**4.55**	2008	0.19	**5.39**	2010	0.14	**4.70**
Giant Grenadier CPUE (number)	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*
Study Area	2002	0.18	**4.37**	2004	0.29	0.00	2008	0.14	**5.00**	2010	0.25	**9.44**
Shelf Zone	2002	N/A	N/A	2004	N/A	N/A	2008	N/A	N/A	2010	0.11	**4.70**
Slope Zone	2002	0.19	**3.76**	2004	0.32	**9.57**	2008	0.09	**2.68**	2010	0.24	**6.28**
Northern Portion	2002	0.09	1.43	2004	0.14	2.95	2008	0.02	0.99	2010	0.07	1.65
Southern Portion	2002	0.14	**3.26**	2004	0.14	**5.44**	2008	0.14	**4.22**	2010	0.09	**3.41**
Pacific Ocean Perch CPUE (number)	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*
Study Area	2002	0.02	0.93	2004	0.04	**2.03**	2008	0.03	1.15	2010	0.09	**3.47**
Shelf Zone	2002	N/A	N/A	2004	0.03	**1.99**	2008	0.02	1.18	2010	-0.01	0.27
Slope Zone	2002	0.02	0.83	2004	-0.02	-0.03	2008	-0.02	0.01	2010	0.13	**2.18**

Northern Portion	2002	N/A	N/A	2004	N/A	N/A	2008	N/A	N/A	2010	0.09	1.73
Southern Portion	2002	0.03	1.45	2004	0.03	**2.21**	2008	0.04	1.75	2010	0.05	**2.24**
Walleye Pollock CPUE (number)	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*	Year	*Moran's I*	*z-score*
Study Area	2002	0.26	**6.37**	2004	0.08	**3.21**	2008	0.30	**8.08**	2010	0.18	**4.41**
Shelf Zone	2002	0.26	**5.43**	2004	0.13	**0.13**	2008	0.31	**7.02**	2010	0.19	**3.90**
Slope Zone	2002	-0.16	-1.11	2004	0.00	0.57	2008	0.33	**4.03**	2010	0.10	**2.12**
Northern Portion	2002	0.27	**4.53**	2004	0.00	0.22	2008	0.30	**4.44**	2010	0.12	**2.49**
Southern Portion	2002	0.09	1.84	2004	0.11	**4.42**	2008	0.05	1.73	2010	0.08	1.51

Table 2. General *G* values by study area, shelf and slope zone and northern and southern portions by year.

Total Groundfish CPUE (number)	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*
Study Area	2002	0.03	**-2.09**	2004	0.04	**-2.43**	2008	0.03	**-3.34**	2010	0.04	-1.39
Shelf Zone	2002	0.04	-0.43	2004	0.06	-1.68	2008	0.04	-1.74	2010	0.05	-1.62
Slope Zone	2002	0.07	-0.34	2004	0.07	-1.31	2008	0.07	-0.34	2010	0.08	0.05
Northern Portion	2002	0.06	0.33	2004	0.07	-0.61	2008	0.05	**-2.38**	2010	0.07	-0.20
Southern Portion	2002	0.06	**-2.95**	2004	0.09	**-2.65**	2008	0.08	**-2.20**	2010	0.11	-1.44
Flathead Sole CPUE (number)	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*
Study Area	2002	0.04	1.72	2004	0.04	-0.90	2008	0.03	-1.26	2010	0.05	0.33
Shelf Zone	2002	0.05	1.17	2004	0.06	-1.26	2008	0.04	-1.06	2010	0.06	0.00
Slope Zone	2002	0.11	**2.31**	2004	0.07	-1.13	2008	0.08	0.75	2010	0.08	-0.10
Northern Portion	2002	0.08	**2.60**	2004	0.07	1.10	2008	0.06	-0.20	2010	0.10	**2.54**
Southern Portion	2002	0.09	0.43	2004	0.10	**-1.99**	2008	0.08	-1.90	2010	0.11	-0.89
Giant Grenadier CPUE (number)	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*
Study Area	2002	0.09	0.29	2004	0.10	0.30	2008	0.08	0.09	2010	0.11	0.68

Shelf Zone	2002	N/A	N/A	2004	N/A	N/A	2008	N/A	N/A	2010	0.69	1.86
Slope Zone	2002	0.09	1.34	2004	0.11	**3.09**	2008	0.08	1.51	2010	0.12	**3.83**
Northern Portion	2002	0.15	1.45	2004	0.18	**2.32**	2008	0.16	0.98	2010	0.18	1.22
Southern Portion	2002	0.20	0.47	2004	0.17	-1.23	2008	0.15	-0.90	2010	0.15	**-2.00**
Pacific Ocean Perch CPUE (number)	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*
Study Area	2002	0.02	-0.80	2004	0.02	-1.36	2008	0.06	-0.40	2010	0.19	0.83
Shelf Zone	2002	N/A	N/A	2004	0.05	-1.51	2008	0.02	-0.95	2010	0.05	-0.95
Slope Zone	2002	0.00	-0.66	2004	0.02	-0.99	2008	0.07	-0.04	2010	0.23	**2.25**
Northern Portion	2002	N/A	N/A	2004	N/A	N/A	2008	N/A	N/A	2010	0.41	1.60
Southern Portion	2002	0.03	-0.87	2004	0.04	-1.40	2008	0.11	-0.45	2010	0.17	-0.25
Walleye Pollock CPUE (number)	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*	Year	*General G*	*z-score*
Study Area	2002	0.06	**2.85**	2004	0.03	-0.98	2008	0.05	1.12	2010	0.06	**2.66**
Shelf Zone	2002	0.06	**2.01**	2004	0.04	-1.21	2008	0.06	0.43	2010	0.07	1.92
Slope Zone	2002	0.05	-0.56	2004	0.02	-0.73	2008	0.22	**2.87**	2010	0.25	2.89
Northern Portion	2002	0.11	**3.45**	2004	0.05	-0.37	2008	0.08	**3.44**	2010	0.08	1.40
Southern Portion	2002	0.05	-0.89	2004	0.09	-0.80	2008	0.06	-0.78	2010	0.09	-0.09