Trends in the Alaskan Bottom-Trawl Fishery from 1993-2015: A GIS-based Spatiotemporal Analysis

by

Carrie Elizabeth Steves

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To my husband, Christopher Jacobson, for providing love and support as I pursue my goals

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List of Abbreviations

AFSC	Alaska Fisheries Science Center
CDO	Climate Data Operators
CP	Catcher/Processor
CPA	Catch Per Area
CPUE	Catch Per Unit Effort
DOM	Dynamic Ocean Management
EEZ	Exclusive Economic Zone
EFH	Essential Fish Habitat
GIS	Geographic Information System
HCA	Habitat Closure Area
NCO	NetCDF Operators
NMFS	National Marine Fisheries
NOAA	National Oceanic and Atmospheric Administration
NPFMC	Northwest Pacific Fisheries Management Council
NSIDC	National Snow and Ice Data Center
MPA	Marine Protected Area
SSI	Spatial Sciences Institute
USC	University of Southern California

Abstract

The Bering Sea, Aleutian Islands, and Gulf of Alaska yield one of the largest sustainable fishing industries in the world. To ensure continued sustainable practices, the effects of fishing activity on the health of the ecosystem should be studied actively. Bottom-trawl gear is a sustainability concern because it directly interacts with the benthic layer. Impact from bottom-trawl fisheries is difficult to assess, particularly over the long-term. Using fishery-dependent observer data from National Marine Fisheries (NMFS) provides insight on the location and the intensity of fishing effort, which can identify areas most exposed to fishing pressure. In this study, the spatial and temporal extent of Alaskan bottom-trawl fishing effort in the Bering Sea, Aleutian Islands, and Gulf of Alaska as defined by NMFS data collected between 1993 and 2015 was explored in a space-time cube in ArcGIS Pro v1.4.1. The variables analyzed were number of hauls per area and total catch per area. Statistical techniques were used to examine spatiotemporal autocorrelation and clustering in these data. Results indicate that fishing effort was non-randomly clustered over space and time (Moran's I, and exact result and probability). A three-dimensional hot spot analysis shows which areas were most intensely fished and illustrates the long-term trends over the study period. The data were then compared with two external factors, sea ice concentration and closed marine protected areas, to determine the effect of changing regulations and climate on fishing activity. The analysis uses long-term retrospective data to examine changes in fishing effort over time in the Alaskan bottom-trawl fishery. The implementation of new MPA's in previously fished areas caused a shift in fishing effort to the still open border areas. Sea Ice had a limited effect on fishing effort spatial patterns, but certain areas in the Bering Sea exhibited increased fishing effort in years with less sea ice effect.

Chapter 1 Introduction

The use of bottom-trawl fishing gear in the Bering Sea, Aleutian Islands, and Gulf of Alaska is controversial because heavy ropes and nets directly interact with the benthic layer and benthic species. The full consequences of continued disturbance on both the environment and the economy is not well understood. Research studies on bottom-trawl fisheries are difficult and expensive to complete (Kaiser et al. 2016). Using fishery-dependent data is one way to overcome these obstacles and to better understand the location and intensity of bottom-trawl impact.

The direct environmental impact of bottom-trawling increases proportionally with increased fishing effort and intensity (National Research Council Staff 2002). The spatial analysis of commercial bottom-trawl fishing effort in the Bering Sea, Aleutian Islands, and Gulf of Alaska used in this project shows the locations with the most intense fishing pressure. This analysis also shows how the fishery has evolved over time in response to changes in the environment and to changes in regulations. The findings will increase understanding of the spatiotemporal patterns of the bottom-trawl fishery in Alaska.

1.1. Study Site

The Bering Sea, Aleutian Islands, and Gulf of Alaska are the focus of this project because they represent a very large portion of the United States fishing industry. The fishing industry in this area is relatively new compared to fisheries in other parts of the world, and no fisheries in Alaska have fully collapsed due to overfishing. The full study area is shown in Figure 1 with important features and major ports identified. These features are used throughout the paper to discuss the locations of spatial patterns. Graticules are given in Figure 1 to show which direction is north. The graticules are omitted in future graphics for visually clarity, but the projection and orientation seen here is used throughout the document.

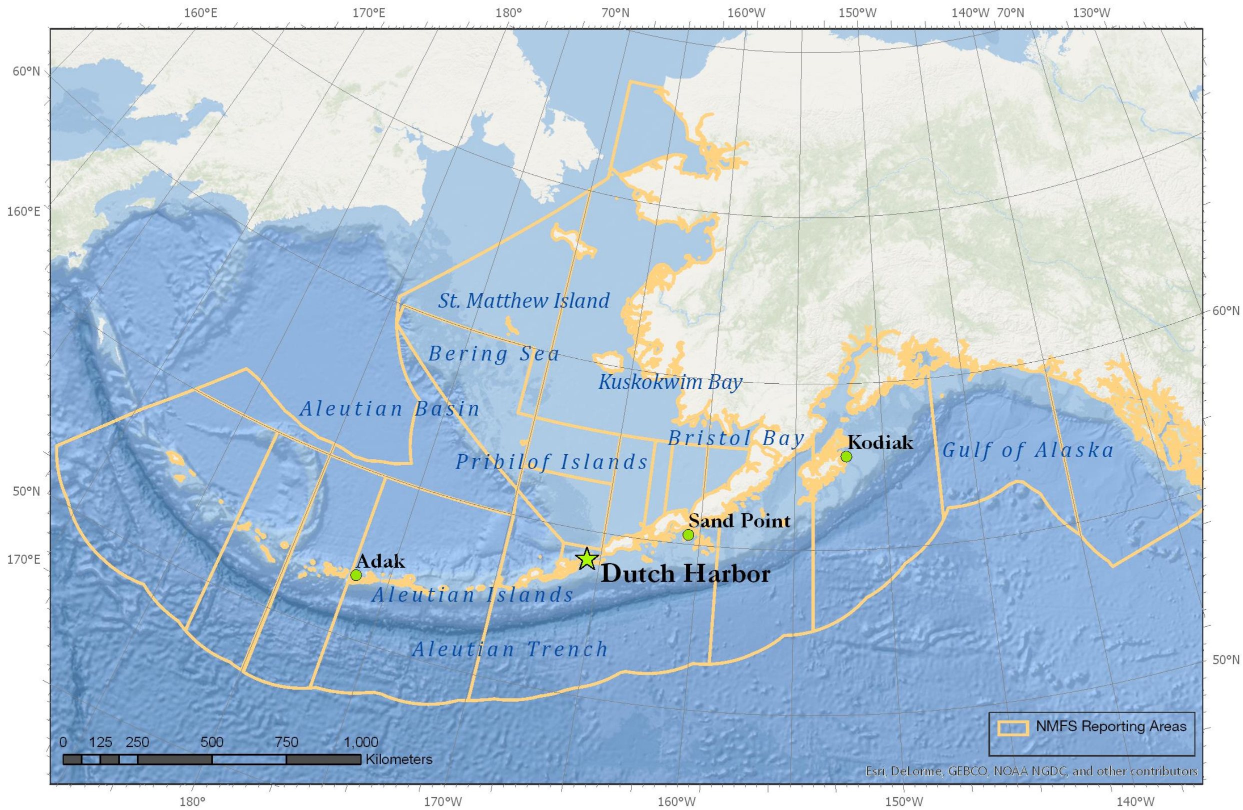

Figure 1. Study site

The Bering Sea is one of the most biologically productive ecosystems in the world, supporting a wide variety of economically important fisheries. The sustainability of these fisheries depends on policies that are informed by continued research of fishery impact on the ecosystem that supports this large and diverse industry. Geographic Information Systems (GIS) are an increasingly important tool in the study and management of marine fisheries (Wright and Scholz 2005). Increased understanding of spatial and temporal patterns through GIS can help to devise policies that will assure the longevity of this important marine ecosystem.

The Bering Sea is semi-contained and consists of the large continental shelf between Russia and Alaska, extending north to the Bering Strait and bordered on its southern edge by the Aleutian Islands. The Bering Sea is subject to seasonal ice coverage that normally forms in December or January, with the peak extent usually occurring in February or March. The maximum extent can be as far south as 58°N. During the summer months, sea ice recedes leaving the area completely free of ice cover. The presence of seasonal sea ice is a driving factor of the ecosystem as a whole. The underlying ocean water remains un-warmed throughout the coverage period creating a "cold pool" that drives currents throughout the summer months affecting all levels of productivity (Hunt et al. 2002).

Most of the Bering Sea continental shelf is relatively shallow with soft benthos, consisting of mostly sand and silt (NPFMC 2015). Areas along the continental shelf and islands become rockier and more complex, creating a home for deep-sea corals and a more diverse population of benthic and pelagic species (Miller et al. 2012). The area surrounding the continental slope is known as the "green-belt" of the Bering Sea and is the most productive part. It also sustains the highest levels of fishing activity. Several deep-sea canyons have been discovered in this area, although very little is known about the invertebrate species composition of these features. The canyons' geological features are likely to support a large array of deep-sea hard corals (Rooper et al. 2013).

The Gulf of Alaska spans from the southeastern peninsula of Alaska and out to the edge of the western peninsula including most of the southern coast and Kodiak Island. This area is unaffected by the presence of persistent seasonal sea ice cover. The Gulf of Alaska contains 24 ecologically-important seamounts and a series of deep-sea troughs, which are thought to be home to a large variety of corals (Stone and Shotwell 2007).

The Aleutian Islands consist of an arced chain of 150 islands that create a porous barrier between the Bering Sea and the larger Pacific Ocean circulation. The continental shelf is much narrower and rockier in this area compared to the Bering Sea. Most fishing activity in the Aleutian Islands occurs in this smaller shelf area, around which depths drastically increase

(NPFMC 2015). Due to its diverse underwater terrain, the Aleutian Islands are also home to a complex array of benthic habitats, and according to habitat modelling efforts, may be one of the richest deep-sea coral beds in the United States (NOAA 2016).

1.2. Bottom-Trawl Impact

Bottom-trawl gear physically interacts with the seabed and benthic habitats, causing direct adverse effects, including loss of habitat and removal of non-target species; and indirect adverse effects, including loss of productivity and species composition changes (National Research Council Staff 2002). The magnitude of impact greatly depends on the duration and intensity of trawl towing. Kaiser et al. (2016) identified “spatial and temporal extent” and the variation of intensity of fishing effort as a high priority “knowledge-need” to better understand the sustainability of bottom-trawl fisheries.

Benthic species are susceptible to damage by trawl gear as the gear directly sweeps through the upper layer of the seafloor. Deep-sea corals are highly susceptible to damage from mobile gear, which physically uproots and destroys the organisms. Hard corals are slow-growing and require long periods, possibly decades, to recover from such disturbance (Stone and Shotwell 2007).

The bottom layer of the ocean is a critical part of the trophic cycle and species assemblage in the upper layers. The effects of disturbing large portions of the seabed and removing of biomass from the benthic layer is not well studied. These removals could cause changes in species assemblage and productivity in areas with intense fishing. The benthic layer is an integral link in energy flow between the different trophic levels within the Bering Sea ecosystem (Wang et al. 2014). Knowing when and where the seabed is most exposed to fishing activity is an important step to the continued study of bottom-trawl fishery impact on the ecosystem as a whole.

Other commercial fisheries are also affected by bottom-trawl impact. The size and age structures of several commercially targeted fishes have been altered due to fishing-related pressures on the population structure (Cardinale et al. 2009). In addition, much of the benthic population consists of juvenile fish and crabs that will later enter the commercial fishery as targeted catch. One concern for industry is that bottom-trawl fisheries deplete stocks of important commercial species, such as Red King Crab, and reduce the future sustainability of those fisheries. As protected areas were introduced to protect these and other important species, the bottom-trawl fishery was forced to change fishing behavior.

Fish populations and species assemblages at all trophic levels have changed in subtle ways due to chronic disturbance from fishing gear. The full effects of long-term bottom-trawling are poorly understood due to the difficulty of study. This study focuses on the spatiotemporal trends of bottom-trawl gear intensity as a direct indication of increased fishery impact.

1.3. History of the Bottom-trawl Fishery in Alaska

The spatial extent of the bottom-trawl fishery has changed significantly over time. The first bottom-trawling vessel arrived in the Bering Sea in 1929 from Japan, and the Alaskan groundfish fishery continued to be largely dominated by foreign-owned vessels until the establishment of the Magnuson-Stevens Act in 1976. Through the Magnuson-Stevens Act, waters within 200 miles of the coastline were designated as the United States Exclusive Economic Zone (EEZ). The U.S. trawl industry began to develop rapidly after and included improvements in technology and efficiency that allowed them to increase the spatial footprint of bottom-trawling in the Bering Sea (National Research Council Staff 2002). Activity peaked in the 1990s.

Concerns of overfishing caused dramatic changes in how the fishery was managed through a series of amendments to the Magnuson-Stevens Act. Agencies began to identify Essential Fish Habitat (EFH) to ensure protection of important spawning and feeding grounds. In 2005, large sections of the Bering Sea were designated as protected habitat areas and prohibited the use of bottom-trawling gear. In 2007 additional closures were enacted to effectively "freeze" the footprint of trawling operations, excluding all areas that had not been recently trawled (NPFMC 2015).

These protective measures led to decreased intensity of bottom-trawl fishing effort and reduced the total geographic area affected in the Alaskan EEZ. Despite the reduced impact achieved, adverse effects of trawling on benthic species and essential habitat continue to be listed as a research priority for the North Pacific Fisheries Management Council (NPFMC) and the National Marine Fisheries Service (NMFS). Recent studies have focused on identifying deep-sea coral beds, benthic nurseries for sharks, skates, and other species, and key habitat for juvenile king crab species (NPFMC 2016). Describing fishing activity and its location in space and time is the first step in achieving these research goals.

The bottom-trawl fishing fleet in Alaska is both large and diverse. Bottom-trawling vessels target a variety of near-benthic groundfish species, including Pacific Cod (*Gadus microcephalus*), Yellowfin Sole (*Limanda aspera*), and other flatfishes. These vessels range in size from small shore-based vessels, to large Catcher-Processors (CPs) that process and freeze catch while fishing is in progress, and offload a completed product. Otter trawls are the most common bottom-trawling gear used in the groundfish fishery. The net can be up to 200 m long and keeps contact with the seabed creating a visible sweep and sediment cloud as it drags. The magnitude of this industry increases the cost of failing to ensure the fishery continues to be a sustainable resource in the Bering Sea, Aleutian Islands, and Gulf of Alaska.

Trawl vessels are closely monitored by the at-sea NMFS groundfish observer program, which began monitoring foreign vessels in 1973 and domestic vessels in 1986. Since its inception, the NMFS observer program has been greatly expanded to ensure the collection of reliable fishery management data. NMFS observers collect location coordinates of the deployment and retrieval of fishing gear and make independent catch estimates. This unique monitoring program resulted in a large fishery-dependent dataset which allows for an in-depth look at the trawl fishery over several decades. Observers are trained by NMFS to collect non-biased random samples, and sample data are extrapolated to provide estimates for those hauls that were not observed (AFSC 2017). This ensures that the data was independently collected and covers most bottom-trawl vessels and hauls in Alaska (AFSC 2017).

1.4. Summary

In this study, the spatial “footprint” of the Alaskan Bottom-Trawl fishery is described by compiling National Marine Fisheries Observer data in ArcGIS Pro v1.4.1. The data were organized into a space-time cube to better analyze the dataset in space and time. The space-time cube was then used to determine overall trends in fishing effort using the Mann-Kendall trend test and to identify fishing effort hot spots using the Getis Ord* statistic. The hot spots identify areas with high bottom-trawl fishing intensity and consistency. The Moran’s I statistic gives a score of spatial autocorrelation that indicates how dispersed or clustered the dataset is compared to a random distribution.

The document is organized into five chapters: Introduction, Related Work, Methodology, Results, and Discussion and Conclusion. Chapter 2, Related Work, reviews the role of GIS and hot spot analyses in past fisheries research and describes how past research influenced this study. Chapter 3, Methodology, outlines in more detail the structure of the data used and all the steps taken to complete the analyses. Chapter 4, Results, describes the findings of each analysis as outlined in the previous chapter. Chapter 5, Discussion and Conclusion, gives further explanations based on the results and describes the successes of the methods used and ways the methods could be improved.

Chapter 2 Related Work

The marine environment is both expansive and complex, making GIS one of the most important tools for future research. GIS provides the base for integrating large datasets describing ocean surface conditions, currents and gulf streams, biological movements, human interactions, habitat mapping, and many other applications. The availability of tools and information has opened new ways to research and manage the world's fisheries in more dynamic and responsive ways (Wright and Scholz 2005).

This chapter seeks to provide context on how this study fits within past research. Section 2.1 describes several important studies that implement spatiotemporal analyses of fisheries effort in the form of hot spot analyses and spatial histories. Section 2.2 describes the benefits and disadvantages of several different measures of fishing effort. Section 2.3 addresses some examples of Marine Protected Areas (MPAs) research, and Section 2.4 addresses Seasonal Sea Ice as it relates to this study.

2.1. GIS in Fisheries

The application of GIS to the marine environment has opened the door to new methodologies and new ways to explore a very large and vital portion of the earth that can still be considered largely unknown. The complexity and fluctuations of the oceans brought a new set of challenges for geographic scientists. Topics of marine GIS range from the physical and chemical oceanography to large dynamic ecosystem and the interactions between both. Complex spatiotemporal data models became a necessity. For fisheries science, the key questions are when and where ocean resources exist, and when and where fishing activity occurs.

Globally, sustainable fishing is at the forefront of providing food for an ever-growing population, while ensuring that it is available for future generations. The goal is to protect not only the food resources, but also the ecosystem that supports it (Bellido et al. 2011). Thus, many studies focus on the increasing "footprint" of fishing effort as food demand rises and gear becomes more efficient at quickly harvesting resources (Swartz et al. 2010). Following these same goals of sustainability, this study uses the spatial history of the bottom-trawl fishery in Alaska to show if management choices have successfully prevented this process of expansion and depletion.

2.1.1. Hot Spot Analyses

Hot spot analyses are a proven tool in the study of fishing effort. The studies that follow in this section are examples of hot spot analyses that describe spatiotemporal patterns of fishing effort both in regional and global scale analyses and have served to mold the methodology of this analysis of bottom-trawl fishing effort in Alaska.

A hot spot analysis is a statistical method that compares an attribute value with that of a defined local neighborhood. Hot spot analyses such as Getis-Ord Gi* look for local areas that consist of mostly high values or mostly low values. The analysis can be applied to both point and polygon data. The analysis depends greatly on the neighborhood and how it is modelled. The results are given a z-score, which reveals those areas that have unusually high coincidence of high or low values. These areas may not coincide with areas that have the highest original attribute value, but the highest correlation between spatial neighbors.

Jalali et al. (2015) determined the existence of hot spots using Catch per Unit Effort (CPUE) data in the Australian blacklip abalone fishery. The study used Moran's I indices in ArcGIS 10 to show statistically significant clusters exist in CPUE data for three major abalone fishing subzones. Fishing effort in the blacklip abalone fishery is intermittently distributed with certain spatial areas being favored by commercial divers. The study used the Getis Ord Gi* statistical analysis tool to identify hot and cold spots in the abalone fishing effort data. Hot spot trends were shown over four-year periods by creating a cumulative hot spot score for each area. The scale of this study is fine, using high spatial resolution data (1000 square meter cells) collected from individual divers. This method is particularly useful in the study of benthic species, such as the blacklip abalone, that are intermittently distributed across seafloor and reef habitats. The hot spot analysis was then compared to the bathymetry to determine which habitats received the most pressure.

Lewison et al. (2009) used a similar method in a multispecies, ocean-wide scale study of global hotspots in both catch per unit effort and bycatch per unit effort. Moran's I revealed that non-random clusters of fishing effort and bycatch exist in both the Pacific and Atlantic Oceans, and both ocean systems exhibit significant hot and cold spots. While the study uses much lower resolution data, it is unique in its scale. Very few studies consider fishing effort at a global scale, and it clearly illustrates the areas with the greatest exploitation and greatest need for increased bycatch measures.

Intensity of bycatch events (hot spots) is used as a management tool in several commercial fisheries, including the Bering Sea pelagic-trawl pollock fishery, which utilizes Rolling Hot Spot Closures to lower incidental catch of salmon. This type of spatiotemporal management is described by Lewison et al. (2015) as Dynamic Ocean Management (DOM), and could be the best method for reducing bycatch worldwide. The method actively monitors the fishery for bycatch hot spots and enacts temporary closures of the areas in which hot spots occur.

Bjorkland et al. (2015) used NMFS at-sea observer data from the West Coast Groundfish Fishery to analyze the success of "move-on" rules to avoid rockfish bycatch. Move-on rules also require areas to be temporarily closed based on clustering of bycatch events in space and time.

Ripley's K function is used to measure the spatiotemporal intensity of bycatch events using point data (presence or absence of each species of rockfish). Ripley's K function measures spatial autocorrelation of point data at multiple distances showing clustering or dispersion. Intensity is used to determine what scale of closure (size and duration) is most effective in preventing bycatch. This type of active management analysis, however, does not consider historical locations of bycatch intensity that may be more informative for the disturbance-based, chronic impact associated with the bottom-trawl fishery.

Coastal fisheries from around the world were described in a hot spot analysis by Stewart et al. (2010). The study used fishing effort density as an equivalent to fishing intensity to determine the most used areas around parts of Africa, Asia, South America, and North America. The results show that fishing hot spots are more likely to occur near more highly populated areas, which may be used to estimate fishing pressure based on a country's population and length of coastline. This is particularly meaningful in areas where fishery-related data is sparse or non-existent.

The study completed by Maina et al. (2016) also focused on estimating fishing effort and describing fishing grounds. Trawl survey data and environmental factors were used to estimate presence of species and catch levels. These data were then used to identify hot and cold spots for fifteen different species targeted by the Greek bottom-trawling fleet. Hot spots in this study were defined as clusters of high fishing effort and high target species presence, and cold spots were defined as clusters of low fishing effort and low target species presence. The methodology presented effectively describes the fishing grounds for future management and conservation purposes. The spatial interactions between humans, resources, and habitat areas is part of the larger effort to create ecosystem-based management practices for fisheries.

A common thread between these studies is the connection between fishing effort intensity and fishing effort hot spots. A cluster of high values is a more meaningful measure of intensity and impact from fishing activity than the presence of single high values alone. This important connection was used to develop the hot spot methodology used for the analysis of the Alaskan bottom-trawl fishery, which is further described in Section 3.2.4. Each study shows the value in identifying fishing hot spots and how the analysis could benefit fisheries science and management.

2.1.2. Spatial Histories

Spatiotemporal analyses in fisheries are not limited to the hot spot analysis and cluster identification. A variety of methods are used to detect more long-term trends of change and expansion in commercial fisheries. These studies provide insight on the history of commercial fishing, which can be essential in recognizing the spatiotemporal patterns of overfishing, impact, and expansion of fishing activity over the course of its growth and evolution.

An in-depth analysis of the growth and expansion of the Brazilian commercial fishing industry was competed by Port et al. (2016). The study used approximate locations and duration to estimate number of square miles swept by bottom-trawling vessels. This approximation was used as a utilization index to determine the areas most used by commercial fishing. This method was able to show the key economic areas used most consistently and areas where the fleet has expanded. The history spans eight years of effort and catch data of this relatively new industrialized fleet. The expansion of fishing effort into previously unused continental slope areas indicated an environmental concern for the benthic habitats in that area.

Miller et al. (2014) completed a historically-based project on the groundfish fishery along the coast of California, focusing more on the identification of trends rather than specific management issues. The study is long-term, covering data from 1933-2010, and shows how the fishery has evolved through space and time. Focusing on the spatial imprint of the groundfish fishery led to the discovery of long-term trends of expansion. Fishing vessels travel farther, fish deeper, and fish in more inclement weather. Catch and vessel productivity have not decreased over time. It is evident that obtaining fish is becoming more difficult in historically productive areas, and that new areas farther from shore are being used to supplement the traditional fishing areas. In this study, showing the data as a localized phenomenon within small grid cells is important, instead of looking at the California fishery as one large region where fine scale trends of expansion can be overlooked.

On a global scale, Swartz et al. (2010) also describes the expansion of fishing effort through a spatiotemporal history from 1950 to present. The study analyzed the amount of primary production required to sustain global fisheries. This measure considers the tropic level of target catch to better measure the exploitation rate of fisheries. The results indicate that the greatest global expansion occurred in the 1980s and 1990s, and fishery growth is supported by moving into new territories or targeting new species as resources are depleted over time.

Spatial histories of fishing effort provide a more robust background for understanding long-term movements and trends in fishery activity. Historical baselines are needed to reveal signs of shifting or expanding fishing grounds. History can also provide insight on how the productivity of fishing grounds have changed (Cardinale et al. 2011). This knowledge is invaluable for preserving fishing productivity and for preserving the ecosystem that supports it.

2.2. Measures of Fishing Effort

Fishing effort is often studied without spatial components and is used to estimate fish distribution and abundance through statistical models. This method has many problems, but in the absence of other data can provide a baseline estimation. Using fishing effort as a predictor of distribution can potentially overestimate abundance due to the efficacy of the fishing fleet in locating small populations of fish and density-dependent behaviors of fish populations. Fish populations often concentrate in small areas when the population is under stress (Harley, Myers, and Dunn 2001).

Although fishing effort is not always a good predictor of stock abundance, it does accurately portray when and where fishing pressure is most intense. Fishing effort as a spatial indicator is particularly useful for describing the impact of bottom-trawl gear throughout the Bering Sea, Aleutian Islands, and Gulf of Alaska. The spatial distribution of fishing effort is a necessary factor in the management of sustainable fisheries as an added element measuring interaction with the environment beyond catch estimates (Stewart et al. 2010).

The most common measure of fishing activity is Catch per unit Effort (CPUE). For a trawl vessel, one unit of effort would represent a haul—the net being lowered into fishing depth and then retrieved one time. The measure would divide metric tons of catch by number of hauls, giving the catch per each haul for all vessels fishing in a particular area. This method, however, cannot take into account the various sizes of nets. Size, travel range, and catch capacity of the bottom-trawling vessels vary greatly and would skew the results of a spatial analysis. Larger vessels commonly use different areas than smaller vessels, and the data would not be a reliable measure of effort for the Alaskan bottom-trawl study. Jalali et al. (2015) and Lewison et al. (2009) both use a CPUE measurement of fishing effort in their hot spot analyses, but this metric was not pursued in this study.

Alternatively, fishing effort can be correlated with total catch, which shows how much biomass is being removed from a particular area. This could be measured by Catch Per Area

(CPA) in metric tons per km^2 (Miller et al. 2014). This measure is less directly related to physical contact with the seabed, but is useful in discerning impact on commercial stocks and bycatch species.

A simple measure of number of hauls per area relates directly to the number of times a particular area has been swept by trawl gear and is a sufficient method of measuring fishing effort. Haul duration or area swept indicators are also measures of direct impact. Hours towed by each vessel gives information on the intensity of bottom-trawling and its effects (Coon 2006). Start and stop points of each tow often misrepresent the area covered; the vessel has the capability to cover large unknown areas in between. Time each net is in contact with the seabed gives a much more useful measurement of the physical interaction with the seabed. Only the number of hauls and their location are available for use for this study and represents the amount of direct contact with the seabed. It also directly relates to the amount of effort or cost that fishing vessels must use to collect their total catch.

Additional measures of fishing effort involve data for individual vessels that are difficult to obtain due to confidentiality. These measures include density of trawl tracts, which would use individual haul start and stop points (Bellman, Heppell, and Goldfinger 2005), average catch per vessel (Monroy et al. 2011), and number of boats per km^2 (Stewart et al. 2010). While these methods could give higher resolution to this study, the data would have to remain confidential and is not possible to present with the limitations of the public dataset.

After reviewing the various methods and the availability of data, the most useful measurement to analyze bottom-trawl fishing for this study are total catch and number of hauls. These measures prevent the skewing of data due to varying trawl net sizes that could be caused by analyzing CPUE data. They provide two valid measures of fishing effort that relay different information about the impact and intensity of the bottom-trawl fishery. Total annual catch provides data for the amount of biomass removed per area, which indicates removal of both target and non-target species. Number of hauls provides data for the amount of effort and the amount of direct interaction with the seabed. While, this does not account for the total area affected, number of hauls is the best data available for use by this project. By comparing the two results some spatial patterns related to CPUE are visible. Both indicate the intensity of impact on the environment and can be used to evaluate the spatiotemporal trends in Alaska bottom-trawl fishing effort over the study period.

2.3. Marine Protected Areas

Marine protected areas (MPAs) are established to preserve cultural, environmental, and economic resources in the marine environment. In fisheries management, MPAs are used to prevent over exploitation of commercial fisheries resources and are created as part of an ecosystem approach (Witherell and Woodby 2005). The federal waters of Alaska have hundreds of designated MPAs as part of the conservation and management of marine resources. Table 1 shows the dates and names of the Marine Protected Areas (MPAs) that affect the bottom-trawl fishing fleet in the Bering Sea, Aleutian Islands, and Gulf of Alaska. The spatial locations of these closures are provided in Figure 2.

Table 1. Marine protected areas in the Alaska (NPFMC 2016)

Name	Year Effective	Description
State Waters No-Trawl	1986	Closed to bottom-trawling gear year-round
Kodiak Red King Crab Closure	1987	Closed to bottom-trawling gear year-round
Walrus Island	1989	Closed to all fishing year-round
Red King Crab Savings Area	1995	Closed to bottom-trawling unless opened by the NMFS Administrator after Red King Crab guideline harvest level has been established
Pribilof Island HCA	1995	Closed to all types of trawling gear year-round
Cook Inlet Trawl Closure	1995	Closed to bottom-trawling gear year-round
Nearshore Bristol Bay No-Trawl	1997	Closed to all types of trawling gear except for the Subarea, which opens from April 1 to June 15 each year
Southeast Alaska Trawl Closure	1998	Closed to all types of trawling gear year-round
St. Matthew HCA	2001	Closed to bottom-trawling gear year-round
Bowers Ridge HCA	2006	Closed to all bottom contact gear year-round
Aleutian Islands Coral Habitat Protection	2006	Closed to bottom-trawling gear year-round
Aleutian Islands HCA	2006	Closed to bottom-trawling gear year-round
Gulf of Alaska Coral Habitat Protection	2006	Closed to bottom-trawling gear year-round
Gulf of Alaska Slope HCA	2006	Closed to bottom-trawling gear year-round
Alaska Seamount Habitat Protection	2006	Closed to all bottom contact gear year-round
St. Lawrence HCA	2007	Closed to bottom-trawling gear year-round
Nunivak Island, Etolin Strait and Kuskokwim Bay HCA	2007	Closed to bottom-trawling gear year-round
Northern Bering Sea Research Area	2007	Closed to bottom-trawling gear year-round, except exempted permits for research purposes
Bering Sea HCA	2007	Closed to bottom-trawling gear year-round

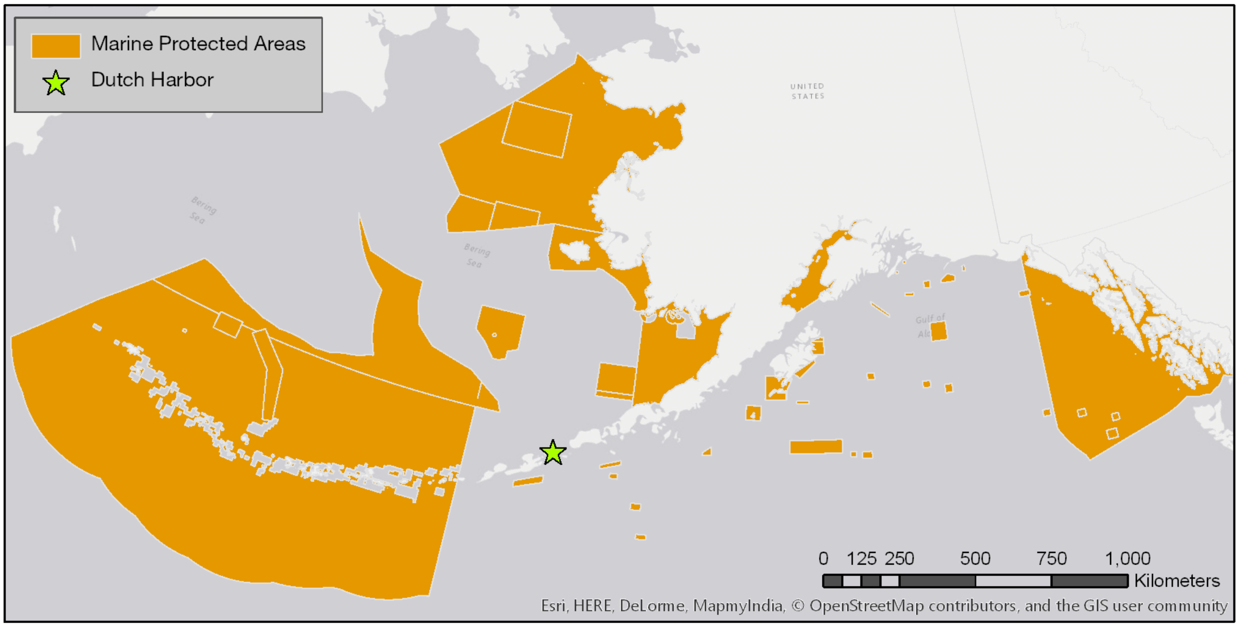

Figure 2. Locations of marine protected areas with restrictions for bottom-trawl fishing

Spatial analysis is a strong component in researching the implementation and utility of MPAs in achieving conservation goals. Spatial models are used to determine boundaries and predict how fishing vessels and communities are affected socially and economically. GIS is often used in fisheries management to measure the effectiveness of MPAs by analyzing changes in biodiversity and CPUE. A full review of the literature surrounding MPA spatial analyses was not completed within the scope of this project, however some examples are discussed in the following paragraphs.

A considerable amount of research focuses on identifying areas for new MPAs, such as the study completed by Harris and Whiteway (2009). GIS overlays of geomorphological, oceanographic and biological datasets are used to define "seascapes," areas that could be considered unique in composition from other areas of the ocean. From these larger seascapes, the most diverse areas were chosen as candidate MPAs using a "focal variety" ranking system. This method required only GIS and existing data for the identification of areas of interest and created a unique ranking system of biological and geological diversity, which MPAs are meant to conserve.

Stelzenmuller et al. (2007) emphasized the importance of spatial trends and spatial autocorrelation when looking at effort data and the effect of MPAs. Spatial patterns of effort exist independently due to the heterogeneous distribution of resources and habitats. These patterns should be considered as part of a larger trend that can be affected by the presence and size of MPAs. The study focused on a MPA located in the Mediterranean Sea, which was used to test the role of the MPA in the conservation of resources. The study determined the protected area had a crucial effect on CPUE, which increases closer to the reserve.

This study focuses on the effect of MPAs on spatial locations of fishing effort by analyzing retrospective data in and around areas that are closed to bottom-trawl fishing gear. Spatiotemporal trends of fishing activity were used to examine displaced fishing effort caused by the closure of fishing areas. In addition to overall trends, hot spot analyses reveal shifts in fishing intensity which may be associated with closures of MPAs.

2.4. Seasonal Sea Ice and Climate Change

Climate change models predict that the temperature in the Bering Sea region will increase by 1 or 2 degrees Celsius by 2040. In this same time period, sea ice is expected to remain highly variable, but the probability of warm years with less sea ice occurring increases over time (Hermann et al. 2015). Changes in sea ice abundance affect the ecosystem and distributions of target stocks in many ways that are beyond the scope of this project. The study simply treats sea ice coverage as areas that are seasonally unavailable to commercial fishing activity.

Decreasing sea ice cover in the Bering Sea could have a major impact on the commercial fishing fleet. The effect of varying sea ice conditions between 1999-2009 in the Eastern Bering

Sea region on CPUE values was assessed by Pfeiffer and Haynie (2012). In addition, the effect of sea ice on the spatial value per metric ton was calculated using catch, prices, and roe recovery rates. Sea ice concentration data from National Snow and Ice Data Center (NSIDC) was used to characterize the availability of fishing grounds during the winter season into ice quintiles. The study indicated some reorganization of fishing effort from warm years to cold years, but overall they found that the majority of fishing effort for all years did not occur in ice-affected areas. Overall, ice-affected areas exhibit a lower expected CPUE and lower profit per ton for both warm and cold years. This is likely the reason for little change in fishing effort patterns on warmer years.

The work by Pfeiffer and Haynie (2012) inspired much of the methodology used here to describe ice cover for the bottom-trawling fishery in the Bering Sea. The bottom-trawl fishing fleet occurs with different timing, different locations and different target species than the pollock pelagic fishing fleet they studied. However, as in their study, the sea ice coverage percentage for each day was used to determine the number of days fishing grounds were available. This measure directly correlates with the annual scale for totals of fishing effort from NMFS observers, and is further described in Section 3.1.2 in the methodology chapter. A historical view of variable ice effect on the spatial distribution of bottom-trawl fishing effort shows how the fleet may react to increased availability of fishing grounds during the winter season.

2.5. Summary

This study draws from past research to produce a successful methodology for analyzing trends in the Alaskan bottom-trawl fishery. Many of these past studies connect the spatial "footprint" of fishing effort as a direct indication of the location and intensity of environmental impact (Russo et al. 2016; Port et al. 2016; Stewart et al. 2010; Kaiser et al. 2016). Each describes the necessity of focusing on the changes of fishing effort patterns in both space and time. This challenge was addressed by choosing the space-time cube organization tool in ArcGIS Pro, which is further discussed in Chapter 3.

The hot spot analyses were also chosen based on past successes by Jalali et al. (2015), Lewison et al. (2009), Bjorkland et al. (2015), Stewart et al. (2010), and Maina et al. (2016). This method is particularly important in identifying areas that were most intensely used by the bottom-trawl fishing fleet in Alaska. Past studies provide a foundation that hot spots exist in fisheries both globally and regionally and are important for understanding locations most impacted by fishing activity.

The spatiotemporal analysis addresses the following six research questions, which are thoroughly examined throughout this document. These questions include:

1. Does Alaskan bottom-trawl fishing effort occur in non-random clusters?
2. Has the intensity of Alaskan bottom-trawl fishing increased from 1993-2015?
3. Has the spatial extent of Alaskan bottom-trawl fishing effort expanded from 1993-2015?
4. How do Marine Protected Area (MPA) closures affect the spatial pattern of Alaskan bottom-trawl fishing from 1993-2015?
5. How does seasonal sea ice affect the spatial pattern of the Alaskan bottom-trawl fishing effort from 1993-2015?
6. Is the space-time cube analysis an effective tool for analyzing the spatiotemporal patterns of Alaskan bottom-trawl fishing effort from 1993-2015?

The first three research questions seek to describe and define the spatial patterns of fishing effort in the region. The first step in completing this spatial analysis was showing that effort is organized into non-random clusters. After this determination, the clusters were defined and categorized by using a hot spot analysis.

The fourth research question seeks to discover the effect of closed areas on fishing effort. Regulations have greatly restricted the areas where bottom-trawl gear can be utilized, and activity has decreased overall since the 1990s (National Research Council Staff 2002). Closures of Essential Fish Habitat (EFH) and areas that were not trawled recently were included in these more rigorous regulations. The goal of these closures was to reduce bottom-trawl effects with the least economic impact on the fleet. The additional closures may act to shift fishing effort, concentrate the fleet into smaller areas, or may force the fleet to find new areas to fish. By analyzing hot spot intensity and trends of retrospective data, this project reveals areas of the Bering Sea, Aleutian Islands, and Gulf of Alaska that have increased pressure from bottom-trawl fishing due to reduced spatial availability of fishing areas.

The fifth research question evaluates the effect of seasonal sea ice on the movements of the fleet. Variations in seasonal sea ice coverage in the past may be similar to the spatial patterns of fishing effort, as warm years become more frequent (Pfeiffer and Haynie 2012). Areas may become more available to the fleet as the extent and duration of seasonal sea ice diminishes. This increase in available fishing area may create additional environmental impact in areas that were relatively undisturbed by frequent bottom-trawl activity.

Finally, the effectiveness of the space-time cube toolset is evaluated through the successes of this project and areas that could be improved in the future. The space-time cube has not been previously used in this field and needs to be further explored as an option for future research. The capabilities of each tool within the space time pattern mining toolbox are utilized in this analysis.

Chapter 3 Methodology

Fishery-dependent data, such as the NMFS groundfish observer data, allow scientific insight into the bottom-trawl fishery, which would otherwise be challenging and costly to study. In this study, observer data were used to create a spatial description and analysis that is beneficial to understanding the extent and intensity of the Alaskan bottom-trawl fishery. This may lead to the identification of areas of concern that could be used for future research and management decisions without the need for intensive surveying. This section describes the data and methodology used for this project to address these goals.

In this study, observer data are also used to identify significant change in fishing behavior over time. Globally, fishing has changed significantly as fishing grounds are depleted and demand for food increases with the growing population. Climate change causes significant changes in target species distribution and range. By using tools available in ArcGIS Pro 1.4 with the available fishery data, these patterns can be identified and described for use in future research. A space time cube and time animations were used to visually analyze these changes in the Alaskan bottom-trawl fishery. Figure 3 shows a brief overview of the workflow followed to complete this project.

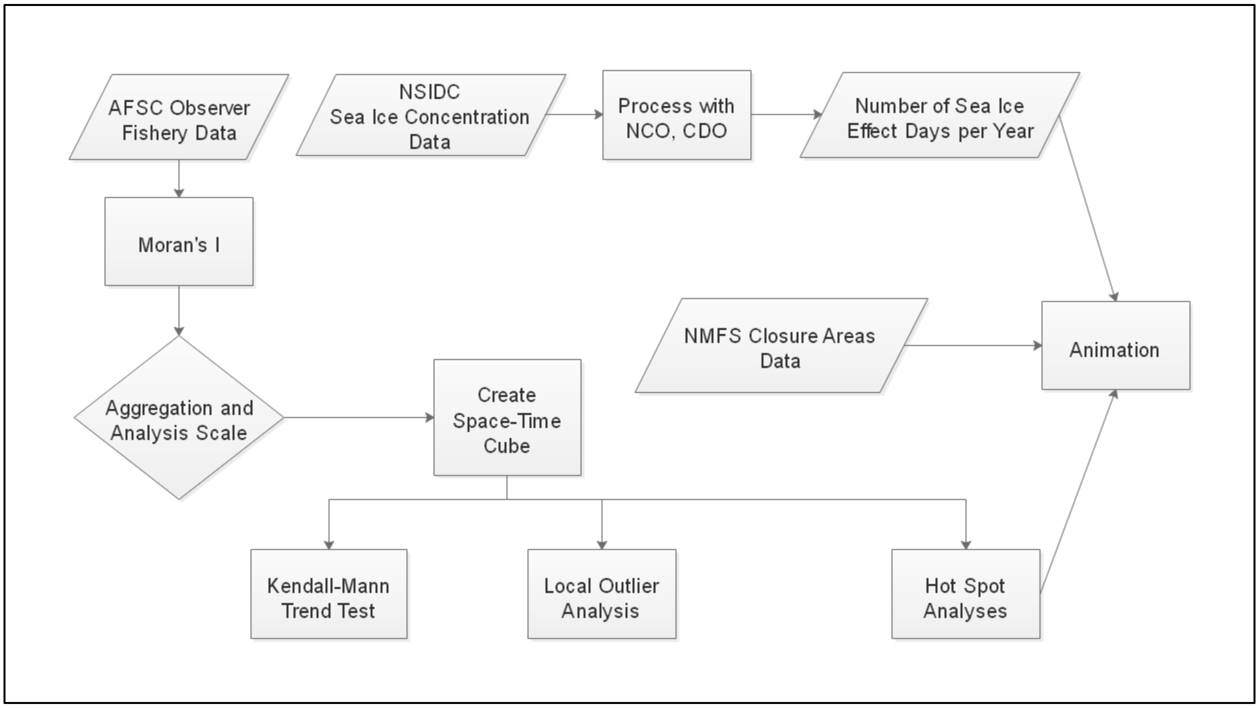

Figure 3. Methods overview

3.1. Data Description

Two important datasets are needed to complete a spatial analysis of Alaskan bottom-trawl fishing effort. Effort is represented in this study by two metrics. First, total catch per area represents the magnitude of the removal of resources including target and bycatch species, and second, number of hauls per area represents the amount of effort by fishing vessels in each area. Both metrics are representative of fishing intensity and are used to describe how this fishery has changed throughout the study period of 1993-2015.

The effect of climate change is shown by using sea ice concentration data as part of this analysis. The presence of sea ice reduces the fleet's ability to utilize an area. Variation in sea ice concentration from year to year is high, but there is an overall reduction in sea ice presence and persistence. Patterns from past years were used to examine how fishing effort changes due to sea ice concentration.

3.1.1. Fishery Data

The data used in this spatial analysis was collected by at-sea National Marine Fisheries observers. These data are not provided in the form of logbooks or from other self-reporting methods. The observers, trained by NMFS, collected haul-level catch and effort information, including exact spatial locations, duration, independent estimates of catch, and species composition. Location data was collected for the beginning and end of each haul using the vessel's navigational equipment. The observer data collection covers a large range of vessels and target fisheries, providing an in-depth look at fishing activity in Alaska. Only those vessels carrying observers are included in the dataset. This fishery-dependent dataset should not be considered a representation of exact totals, but does give a general description of when and where bottom-trawl fishing occurred that is acceptable for this study (AFSC 2016).

3.1.1.1. Effort

The NOAA Alaska Fisheries Science Center (AFSC) supplies aggregated groundfish observer data for public use. The data are distributed in zipped text files, in delimited comma format. The dataset needed for this project is EFFORT.txt, which contains information on how many hauls occurred in a 400 km^2 area, as sampled by NMFS Fisheries Observers and an estimate of total catch in each area. The grid is further discussed below. It was not possible to specify which species were being targeted, since the bottom-trawl fishery is multispecies and can target different species from haul to haul. After extraction, the dataset was imported into ArcGIS as tables. The LON400SQKM and LAT400SQKM were used as the x and y coordinates to create a point feature set for the table. This comprises the main fishery dataset for this study.

Due to confidentiality, AFSC aggregated the data into 400 km^2 cells for public use. Values for any cells with less than three vessels reported were not included in the text file, thus there is no indication which cells had no data and which cells had no fishing. The aggregation reduced the spatial resolution of the analysis and eliminated the opportunity to choose an aggregation level customized for this study. Despite the limitations, observer data is the best fit for an analysis of fishing effort. The NMFS observer data collection is preferred because it is collected directly onboard fishing vessels by non-biased observers. Unlike survey data, it depicts movements and catch of operating vessels.

AFSC also provides POLY400SQKM, which contains a polygon file of the 400 km^2 cells represented by the latitude and longitude centers in the EFFORT dataset. The feature layer shows the size and shape of the cells used to aggregate the observer data for public use. Each cell is slightly different in length and height to reduce the influence of converging meridians in the near polar region of Alaska. Area remains constant at approximately 400 km^2 for each cell. The grid is shown in Figure 4. The projection used for the aggregation was an equal-area Albers projection. It has a latitude of origin of 50 degrees North and the two standard parallels are at 55 and 65 degrees North. It uses the GCS North American 1983 datum. This projection was used throughout the study because the projection was fit specifically to the study area. It also more accurately portrays the areal data used in this study.

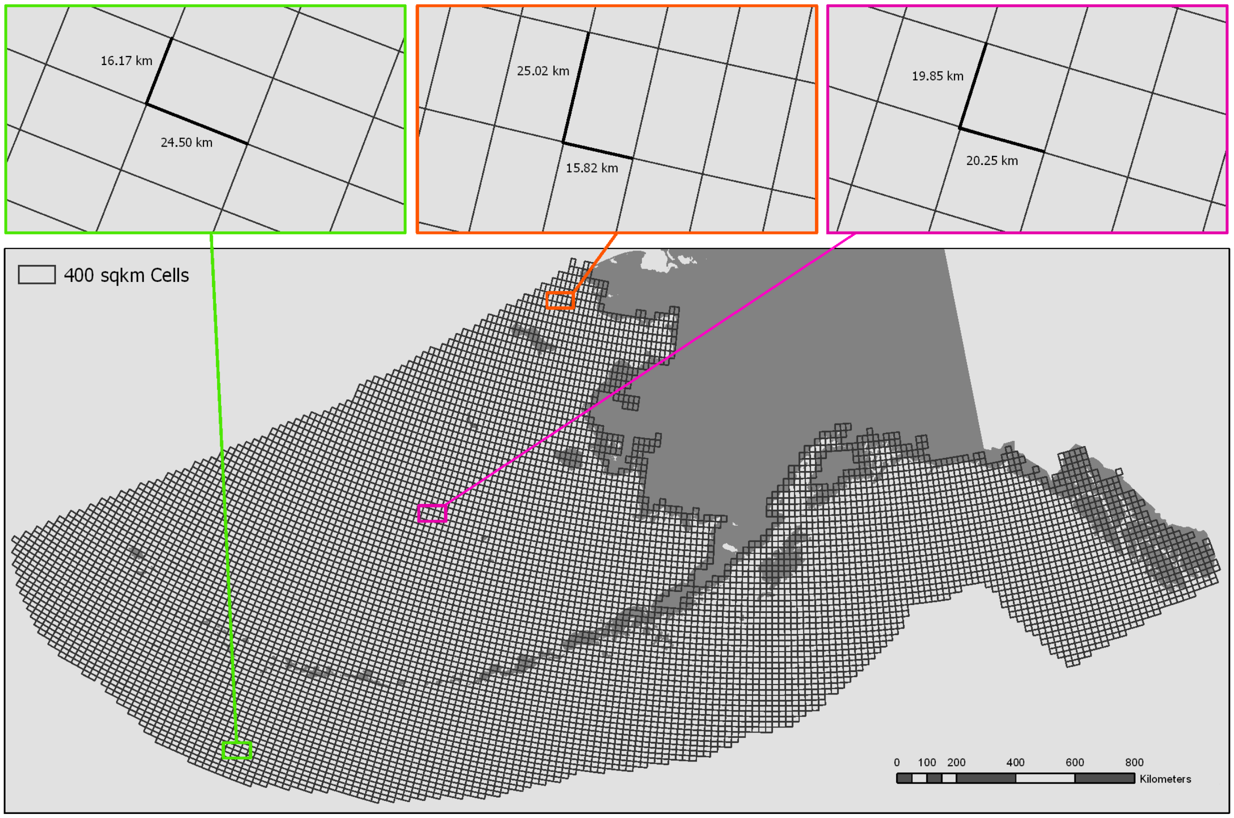

Figure 4. Aggregation format of NMFS observer data

The observer dataset covers over two decades of catch information, from 1993 to 2015 with annual sums of catch and the number of hauls for a large variety of gear types and target species. The effort data file includes 27,555 rows. Through selection, this large dataset was narrowed into a focused study on non-pelagic trawl vessels. The attributes are described in Table 2.

As shown in Table 2, there are two versions of total catch and total hauls, sampled and observed. The SAMOTC and SAMHAULCT represent only the hauls that an observer was able to sample. Although only vessels carrying observers are included in the dataset, circumstances onboard the vessel may not allow for all hauls to be sampled. In this case, the observed total catch and total hauls would differ from the sampled total catch and total hauls. The observed total catch and total hauls include hauls that were not physically sampled by the observer, but the observer was present to account for the estimated catch and number of hauls (AFSC 2017). The observer's estimates of total catch and total hauls (OBSOTC and OBSHAULCT) were chosen for this project. Although it uses estimation of non-sampled hauls, it more accurately represents the activity of each vessel monitored.

Table 2. EFFORT data attributes

Attribute	Description	Measurement	Units
LAT400SQKM	Latitude of the center of the $400km^2$ cell	Interval	Degrees
LON400SQKM	Longitude of the center of the $400km^2$ cell	Interval	Degrees
GEAR	Gear type: longline, pelagic trawl, non-pelagic trawl, pot	Nominal	None
YEAR	The year the data is summarizing	Nominal	Time
SAMOTC	The official total catch estimate from sampled hauls only for all vessels	Ratio	Metric Tons
SAMHAULCT	The number of hauls sampled	Ratio	None
OBSOTC	The observer's estimate of total catch for all vessels and hauls	Ratio	Metric Tons
OBSHAULCT	Number of hauls including both sampled and un-sampled	Ratio	None

The total annual catch dataset and total annual number of hauls are summarized in Figure 5 and Figure 6. Each cell shows the sum of each cell for all years in the study period. Only cells with totals over 0 are included. This gives an approximate magnitude of the number of hauls summarized in each cell and the resulting catch totals for each cell for the observed dataset. The spatial distribution shows that only a relatively small thin area near the coasts of the Aleutian Island and Gulf of Alaska regions are utilized. The Bering Sea shelf is highly utilized, particularly near Dutch Harbor and going up the edge of the continental slope.

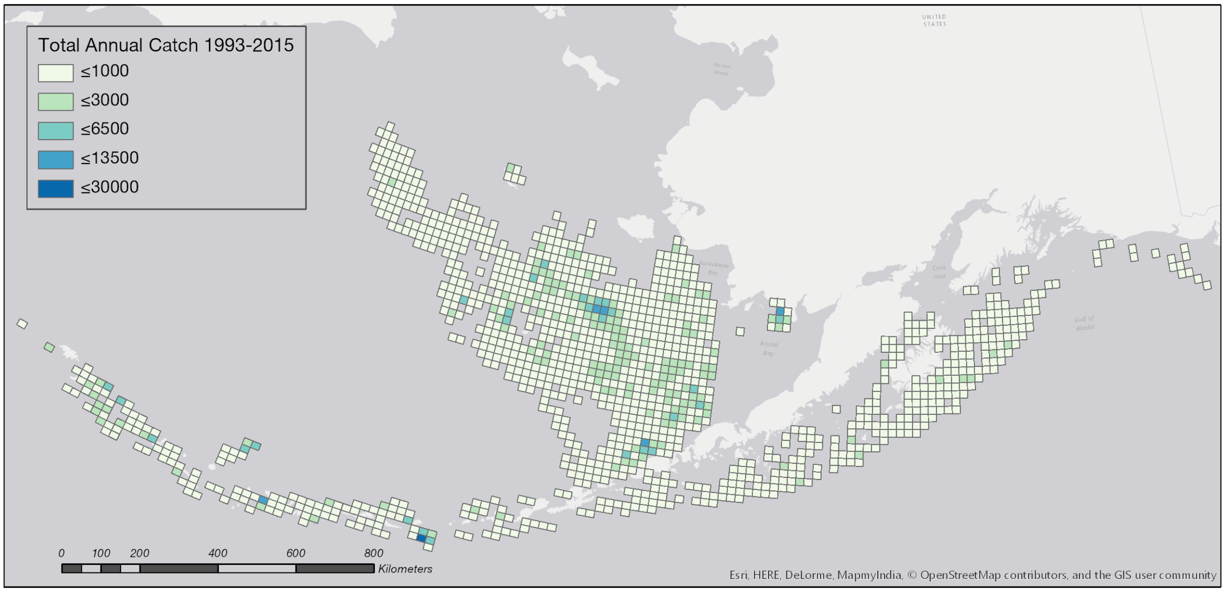

Figure 5. Summary of total annual catch dataset

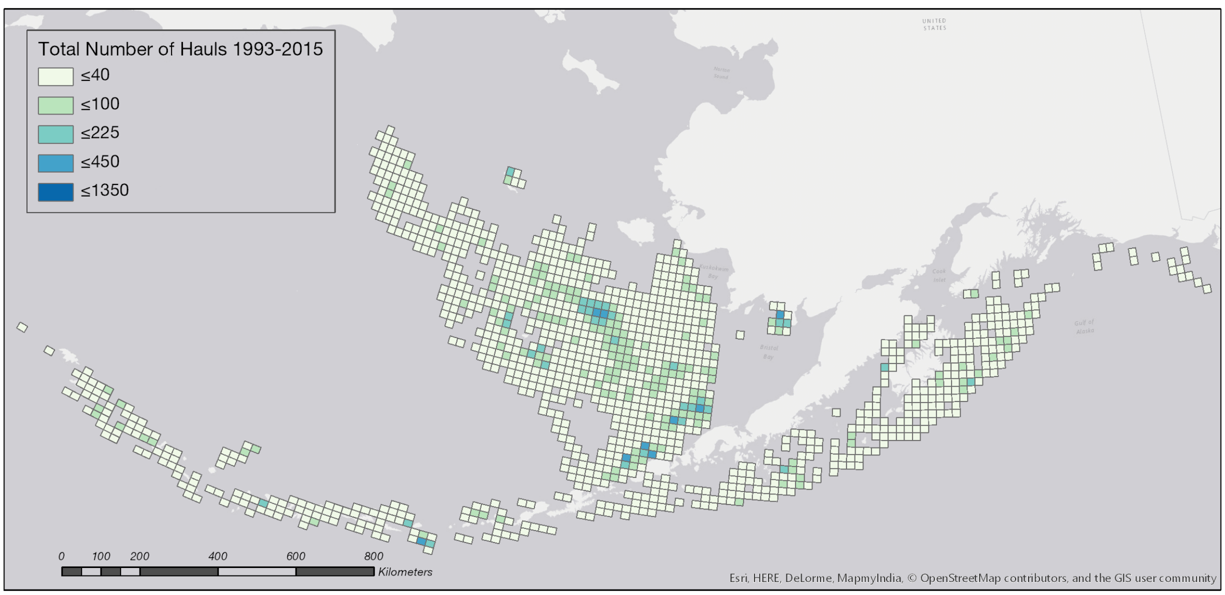

Figure 6. Summary of Total Number of Hauls dataset

3.1.1.2. Closed Areas

Locations and timing of fishery closures provided by NMFS in the form of a shapefile were also used in the assessment of fishing effort. Each closure area in the shapefile table was given a new date effective field, so that it could be used in the time animation and appear at the appropriate time. These dates were found as the date the amendments to the Magnuson-Stevens Act were passed by congress (NPFMC 2016). Only full-time closure areas were included; those that are still seasonally open to bottom-trawl fishing were not included. Areas that may have closed as the fleet met catch or bycatch limits were also not included. Figure 7 shows the closed areas for bottom-trawl fishing that were included in this study.

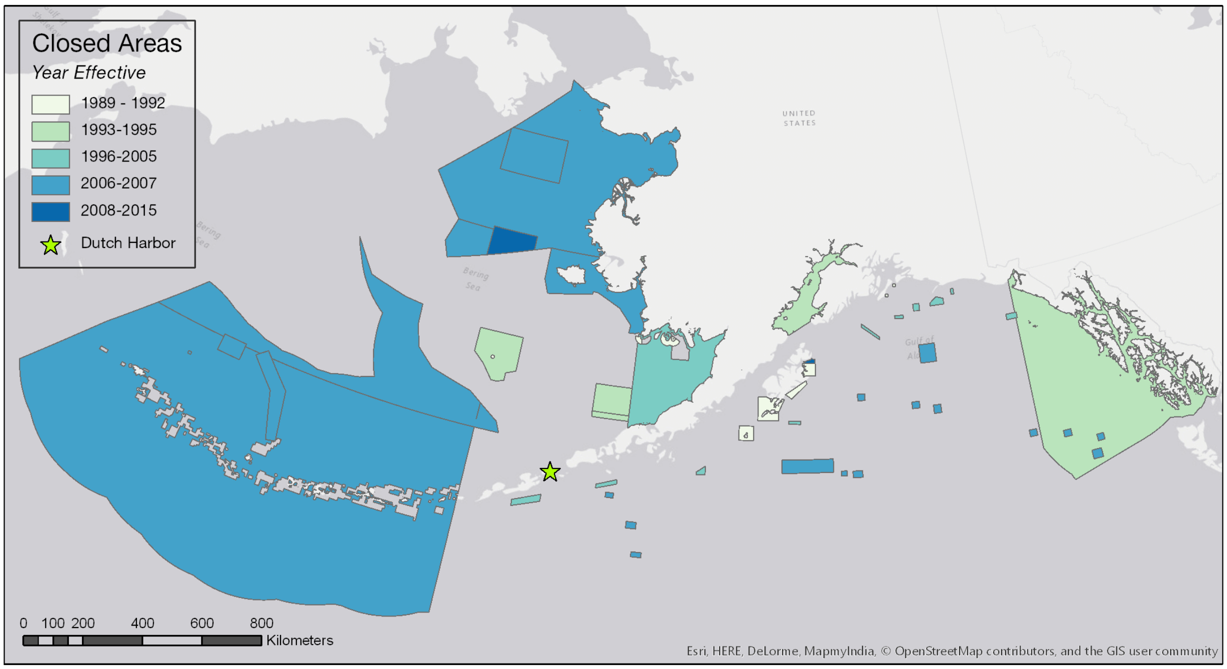

Figure 7. Habitat closure areas dataset classified by year effective

3.1.2. Sea Ice Concentration Data

Sea ice concentration significantly reduces the available area for fishing during the winter season. With sea ice extent and duration expected to decline due to global climate change, significant shifts in fishing intensity and location may result. The bottom-trawl fishing fleet's response to past sea ice anomalies may help with predicting the future impact of climate change in the Bering Sea.

Sea ice concentration data is available through the National Snow and Ice Data Center (NSIDC) and is collected via the Nimbus-7 SMMR and DMSP SSM/I-SSMIS Passive

Microwave satellite instruments (Cavalieri et al. 1996). Images have a 25-km resolution and depict daily sea ice concentration based on brightness and temperature for the entire polar region using the NSIDC Polar Stereographic Projection WGS 1984. The files are stored in NetCDF format. This study required daily files for the full extent of the study site from 1993-2015, which were then processed into a total annual sea ice effect index.

Processing this large set of NetCDF files required the use of two command line packages: Climate Data Operators (CDO) and NetCDF Operators (NCO). Python was used to create an engine that would run through the individual files (one file for each day of all 23 years). Each file was clipped to the spatial range needed for the study area and unneeded attributes were removed. CDO was used to aggregate the data into yearly sums.

Sea ice effect was limited to 20% ice concentration or greater. This number was chosen based on the study completed by Pfeiffer and Haynie (2012), which stated that only minor reclassification of individual cells occurs when using 15% or 30% as the cut-off for sea ice concentration effect. The results of the analysis of CPUE did not differ significantly between 20% and other amounts. NSIDC uses a 15% or greater concentration to represent sea ice existence in measuring sea ice extent. The presence of ice is not representative of a hard line of no-entry for fishing vessels, which can enter ice areas based on personal decisions of the captain. It is more challenging and dangerous to fish in ice-affected areas. Areas with 20% or greater sea ice concentration should not be considered an exact boundary to fishing effort, but a guideline that shows areas vessels are less likely to enter.

For each daily file, a sea ice concentration greater than 20% was given a one value and less than 20% was given a zero value. This new field was then summed by each year. The resulting field contained a value ranging from 0-365, which indicated the number of days per year the area was affected by 20% or greater ice concentration. The summary field revealed how many days per year the area was unavailable for use by the bottom-trawl fishing fleet. A metric of number of days affected by sea ice was used in a similar study by Pfeiffer and Haynie (2012) to analyze the effect of sea ice on the pollock fishery in the Eastern Bering Sea.

After processing the data into annual totals of sea ice days, each yearly NetCDF layer was imported into ArcGIS as a raster file. Each file was then clipped to the area covered by NMFS reporting areas in the Bering Sea, Aleutian Islands, and Gulf of Alaska (as shown in Figure 8). This includes all areas with no removals for zero values or closed areas, except for the Bering Sea HCA, which was closed in 2007 to bottom-trawling and rarely fished before that time. The sea ice data was never integrated with the effort data centroids, but is aggregated into the space-time cube hexagon format, which is described later in this section. Average number of days affected per year over the entire period for the study area is shown in Figure 8.

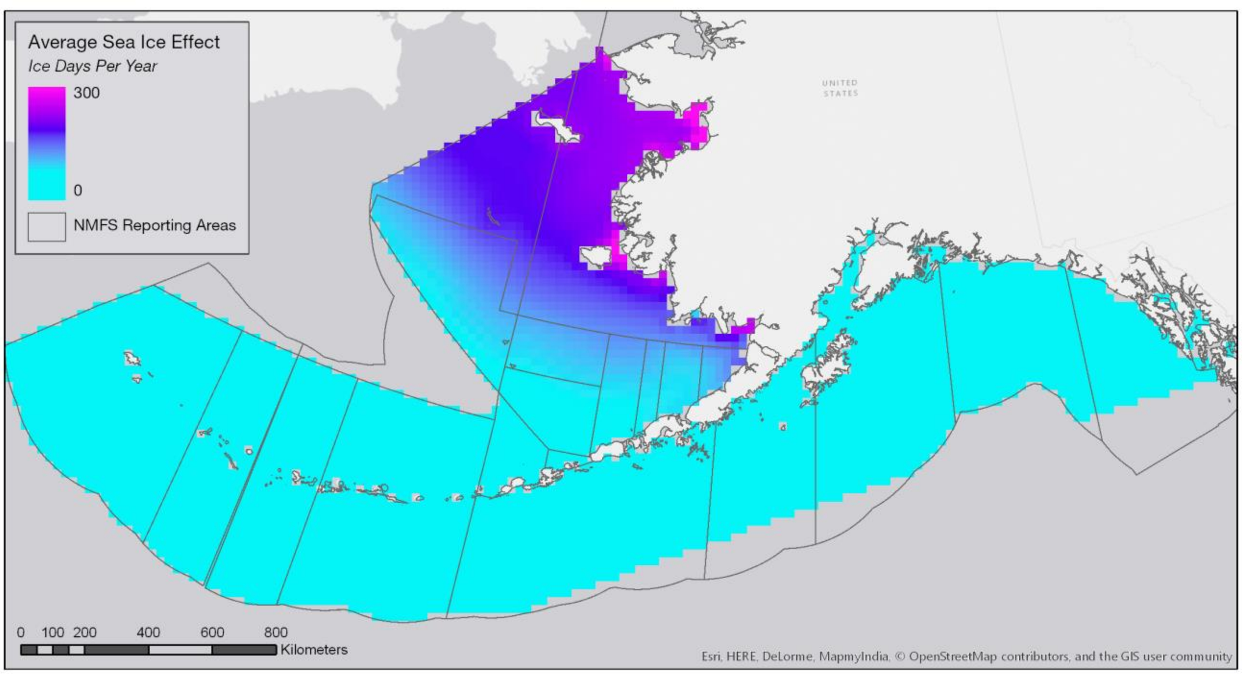

Figure 8. Average sea ice days from 1993-2015

The average of all the data points over the 23-year time span was used to determine high ice and low ice years. High ice years were determined to be at least 0.5 standard deviation above the average annual ice days, and low ice years were determined to be at least 0.5 standard deviation below the average annual ice days. During high ice years, more of the fishing area is affected and for a longer period of time. During low ice years, ice extent and duration is significantly reduced, leaving more area open for fishing for a longer period of time. Number of days per year the fishing area is not available due to seasonal sea ice can be directly related to the annual fishery data to compare high and low effect years and the resulting spatial patterns of fishing effort.

A time-series of isolines representing increments of 50 days of annual sea ice coverage was created from the average of all yearly raster files for use in the animations described in Section 3.2.5. Additional manipulations of the raster dataset were completed to improve comparison and visualization of the sea ice effect data with fishery effort data. The hexagons, which are further described in Section 3.2.2. were used to summarize ice effect for each location. A spatial join using the average of all yearly sea ice effect files was completed. The result provided an average number of ice days for each hexagon, which was used to classify the fishing area into five ice effect zones: No Effect (0 days), Low Effect (1-50 days), Mid Effect (50-100 days), High Effect (100-150 days), and Most Effect (150 or greater days). The zones provide visual boundaries to compare fishing effort between low and high effect years.

3.2. Spatiotemporal Analyses

The spatial “footprint” of the trawl fishery is shown using several exploratory tools in ArcGIS Pro 1.4.1. The resulting analyses show which areas were most intensely fished by bottom-trawl gear and how it changed over time. The two variables used in the fishing effort spatial distribution are Catch Per Area and Number of Hauls Per Area. The intensity and consistency of these variables was described using an emerging hot spot analysis.

3.2.1. Spatial Autocorrelation

The effort dataset was first tested for the existence of non-random clustering of effort levels. The global Moran's I tool gives a measure of spatial autocorrelation, showing that the spatial patterns of fishing effort distribution are not created by random events, but show distinct clustering or dispersion. An index significantly larger than zero shows clustering and an index significantly less than zero shows dispersion. It also provides useful measurement of scale. The incremental spatial autocorrelation tool in ArcGIS gives the Moran's I for several different distance thresholds, designated by the user. The results were used to find the peak level of spatial autocorrelation. The peak level was used as the distance band threshold for the spatial neighborhood of the hot spot analysis. Moran's I was used in several fishery studies to describe clustering patterns of both fishing effort and bycatch incidents (Lewison et al. 2009; Jalali et al. 2015).

The incremental spatial autocorrelation tool was used on each year individually. The tool is unable to take into account the difference between spatial and temporal neighbors. Using all data points from all years created too many neighbors and was not an appropriate way to look at the data. Using individual years did not allow for a single peak distance to be chosen for the entire dataset, but a peak value was calculated for each year individually. This provided a range of peak values for the total annual hauls and total annual catch datasets.

3.2.2. Space-Time Cube

The focus of this project required exploring the trawl fishing effort data in both space and time. Spatiotemporal patterns are difficult to portray through traditional methods, but the space-time cube allows time to be viewed and analyzed as a third dimension, with the spatial locations represented by x and y and time represented by the z-axis. Each year of the fishing data effort is considered as one time slice of the space-time cube. The results of the space-time cube were then further analyzed using the space time pattern mining tool suite, which includes the emerging hot spot analysis tool, the local outlier tool, and the 2D and 3D visualization tools.

To use the space-time cube tools, all data points must be aggregated into individual space-time bins. The bins chosen for this study are hexagonal. The hexagon shape creates more uniform distances between each neighbor and is also preferred for higher latitude study areas because they are less prone to distortion. The unusual spacing and dimensions of the original aggregation grid made it difficult to impose the regular hexagon fishnet onto the data. The hexagon width of 30.39 km was chosen based on area and from the results of the incremental spatial autocorrelation tool. Each hexagon is approximately 800 km^2, double the area of the original 400 km^2 grid of the source data. Doubling the area ensured that at least one grid centroid lands in each hexagon. Once aggregated, 4847 hexagon locations were created, with 790 containing at least one point for one time step interval.

The intensity of bottom-trawl effort is represented by assigning the maximum value of all grid centroids that fall in each hexagon bin in the space-time cube. Thus, each hexagon's value is recorded as fishing intensity, stated in the unit of 400 km^2. By using the maximum, skewing by zeros, no data, and edge areas is reduced, while observed magnitudes are retained.

For the space-time cube, each location must have a data value for each time step. Thus, empty bins must be filled with a zero value. This required some careful consideration of the difference between NoData and 0 values in this dataset. Some areas that were legally open, but not fished, may not have been suitable for fishing for other reasons, such as low-catch rates, rugose terrain, or non-ideal depths. With the unique requirements of the public observer dataset, a zero value could indicate either no fishing occurred or a missing data point from too few vessels using the location. Thus, it was not possible to distinguish in this analysis between no data and missing data. Using a zero-padding method, only bins that were active at least one year of the study time span were zero-padded. Bins that were never active throughout the time span were coded NoData. This reduced the skew that would be caused by using a full zero pad for the entire open fishing area.

3.2.3. Mann-Kendall Trend Test

The space-time cube tool packaged the bin dataset into a NetCDF file with trend data created from the Mann-Kendall trend test. The Mann-Kendall test compares each bin value with the value from the previous year. If the value is greater than the previous year, the bin is given a 1 value. If the value is less than the previous year, the bin is given a -1 value. If there is no change, the bin is given a 0 value. The resulting values for each bin are added together to determine the overall trend. No trend results in a 0 value. Positive or negative scores indicate an overall trend in the data (Esri 2017b). The Mann-Kendall trend analysis is a valuable tool for determining overall trends in data without making too many assumptions about the data itself. It is a non-parametric rating system that is sensitive to slight overall trends rather than assessing the data based on fluctuations from a median value (Cotter 2009). Overall trend values can show many changes in bottom-trawl fishing patterns within the 23-year period of this study.

3.2.4. Hot Spot Analyses

The emerging hot spot analysis technique improves upon traditional hot spot methods by including time. Rather than running a hot spot analysis for each year independently, in emerging hot spot analysis neighbors in both time and space contribute to the determination of a hot or cold spot. The hot spot analysis was completed using the Getis Ord Gi* statistic. This tool compares data in each cell with the surrounding cells within the parameters.

A 79-km distance band was used to determine spatial neighbors, and the spatial neighbors from one time step earlier, excepting the first time step interval, 1993. The distance band was chosen based on the peak value range from the incremental spatial autocorrelation tool results. Each hexagon has a short diagonal of 30.39 km, so the distance band falls within the third hexagon from the center, which matches well with the average peak distance for the total annual catch and total annual haul datasets. The time band was chosen so that the locations of hot spots rely on the current year and the previous year's values, smoothing the changes from year to year and possibly reducing the visibility of sporadic or intermittent hot spots. The two most westerly cells in the Aleutian Chain did not have spatial neighbors within this distance band. The analysis results for these cells were only tested based on temporal neighbors.

Cells that show a statistically significant clustering of many high values were labeled as a hot spot. Cells that show a statistically significant clustering of low values were labeled as cold spots. The hot and cold spots are designated by giving each grid cell in the dataset a corresponding z-score. The results show the relative intensity of trawl fishing activity per cell. The space-time cube was analyzed for both variables: total annual catch and total annual hauls. In addition, a cumulative z-score for each location was calculated using the spatial join tool to sum z-scores over all 23 time periods. This is a measure of cumulative hot spot ranking similar to that used in the study completed by Jalali et al. (2015).

The Anselin local outlier analysis identifies bins that are statistically different from their surrounding neighborhoods. This situation would indicate areas that do not fit with the overall clustering pattern shown in the hot spot analysis or areas that may be causing skewed results in the surrounding areas. The local outlier analysis of the space time cube identifies four categories: Low-Low and High-High indicating low or high values surrounded by similarly low or high value clusters, Low-High indicating a low-value outlier within a high-value cluster, and High-Low indicating a high-value outlier within a low-value cluster (Esri 2017c). An outlier suggests that additional processes are influencing the affected cell and would need further investigation.

3.2.5. Space-Time Visualizations and Animations

Visual identification of spatial patterns is often the first step to discovery and explanations for the underlying processes. The space-time cube allows for many different visualizations that uncover different parts of the same story. Bottom-trawl fishing patterns are governed by many complex factors that would be difficult to model or explain with accuracy. Looking at the larger pattern gives insight into a highly diverse fishing fleet and the spatiotemporal patterns of past years.

Two-dimensional visualizations are extremely useful to display overall changes in the study period. Overall trends of both annual catch and annual number of hauls totaled using the Mann-Kendall ranking system identify areas where trends are most statistically significant. The emerging hot spot analysis, in two dimensions, categorizes each cell based on how often and when the cell has been a statistically significant hot or cold spot (Esri 2017a). The categories are explained in Table 3. Only one category of cold spots was found in the data; the rest of the categories have been omitted from the table.

Table 3. Modified Emerging Hot Spot Categories (from the ArcGIS Tool Reference)

Category	Definition
New or Intensifying Hot Spots	Includes new, intensifying, and consecutive hot spots. New hot spots are significant for the final time step only. Intensifying hot spots are significant for 90% of the time with increasing intensity in the final time steps. Consecutive hot spots are significant hot spots for several consecutive time steps including the final time step.
Persistent Hot Spots	Persistent hot spots are significant hot spots for 90% of the time step intervals, but have no significant trend of increasing or decreasing intensity.
Sporadic Hot Spots	Sporadic hot spots are significant for less than 90% of the time step intervals and at irregular intervals. This category also includes oscillating hot spots, which may have been cold spots or hot spots at irregular intervals and were significant for less than 90% of the time step intervals.
Diminishing or Historic Hot Spots	Diminishing hot spots are significant for 90% of the time step intervals, but have decreasing intensity overall. Historic hot spots are significant for 90% of the time step intervals, but not significant for the most recent time period.
Sporadic Cold Spots	Sporadic cold spots are significant for less than 90% of the time step intervals and at irregular intervals. This category also includes oscillating hot spots, which may have been hot spots or cold spots at irregular intervals and were significant for less than 90% of the time step intervals.

Three dimensional visualizations are particularly useful in displaying the hot spot results. While the hot spot categories are useful in identifying areas of interest, a data stack is a more complete visualization of the spatial location’s history. The space time explorer add-on for ArcGIS Pro was used to create detailed views of areas of interest and allow the cube to be examined from a variety of viewpoints. Rows can be removed to allow the “inside” of the cube to be further explored, or each slice can be removed one by one to dig in from the top down.

Taking the data a step further, an animation of each time slice of hot spots coupled with sea ice days allows a direct visual comparison of the two variables for each year within the study period. Each year is shown in sequential order using time step animation in ArcGIS Pro. Closed areas appear as they are approved and enacted. An animation was created for both measures of effort, haul numbers and total catch. The animations were used to visualize the difference in hot spot locations during different years of low or high ice years.

Chapter 4 Results

Bottom-trawl fishing effort data from NMFS observers was used in a retrospective spatial analysis to test hypotheses about the location and intensity of effort, and how it changed over time. Each test used both the annual total of catch and the annual number of hauls. First, fishing effort was tested for spatial autocorrelation. A global Moran's I statistic was used to determine that fishing effort occurs in non-random clusters. The incremental spatial autocorrelation tool was used to determine the scale at which peak clustering is measured. The positive outcome of the spatial autocorrelation test created the base needed to proceed with additional spatial analysis.

Fishing occurs in a changing, complex environment. Two variables of change were chosen to test their influence on the Alaskan bottom-trawl fishery effort spatial patterns: regulatory closures of fishing areas and changing seasonal sea ice conditions. Regulatory closures may act to concentrate the fleet causing remaining areas to be more intensely fished. Reduced sea ice opens areas for longer periods of time and may increase activity in normally ice-covered areas.

These last two hypotheses were tested using the space-time cube, in which the data was organized into space-time bins. The completed space-time cube was analyzed for overall trends using the Mann-Kendall trend test to determine areas of increased or decreased activity over the study period. Hot spot analyses showed where fishing activity is most intense, and the emerging hot spot analysis showed the intensity and persistence of hot spots over the study period. Both provided insight into an evolving fishery, which has shown significant changes in location and intensity of fishing over the study period.

4.1. Spatial Autocorrelation

The results of the Global Moran's I statistic indicate a strong clustering of similar values with a positive index result for all years, tested separately, for total annual catch and total annual number of hauls. This rejected the null hypothesis of complete randomness and indicated that bottom-trawl fishing effort occurs in non-random clusters.

Incremental spatial autocorrelation tested the Global Moran's I statistic at different distance bands and determined the scale at which the most intense spatial clustering is found. The original centroids of the effort dataset were used, which is aggregated into 400 km^2 cells. The z-score given for each increment was used to find the peak distance for each year of data. These values are shown in Figure 9 and Figure 10. Peak z-score distance bands range from 45,000 meters to 105,000 meters in both the total catch and number of hauls datasets. This is the ideal range for analyzing high and low clusters of the point datasets. Bin size of the space-time cube was set to be below this range, so that patterns would not be lost in the reduced resolution.

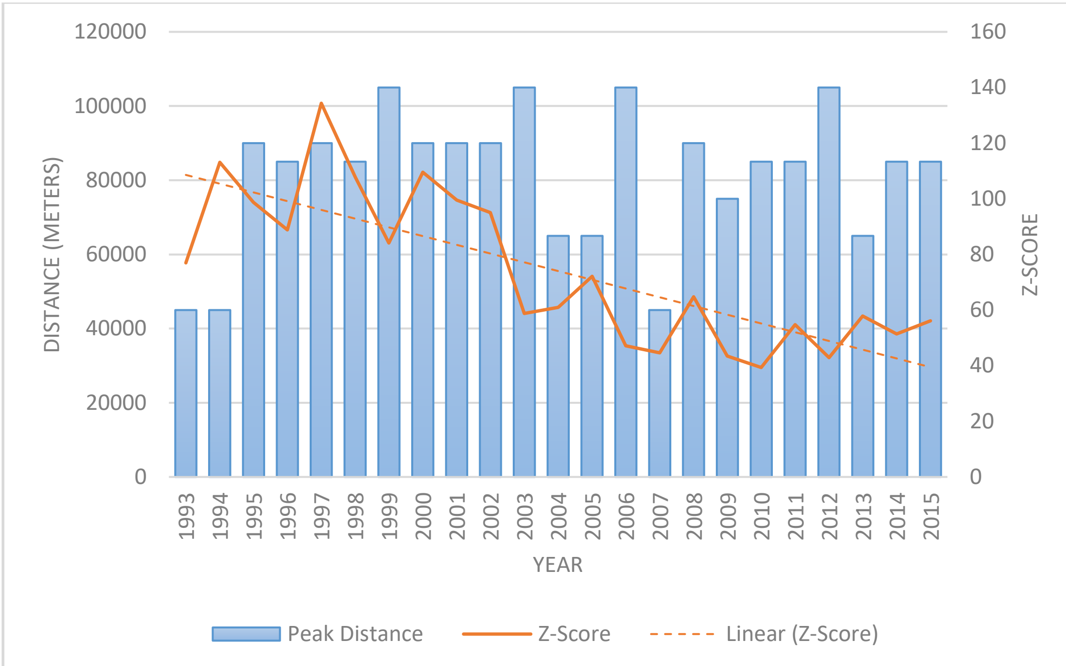

Figure 9. Peak z-score values for each year of Total Annual Catch and the distance band associated with the peak value

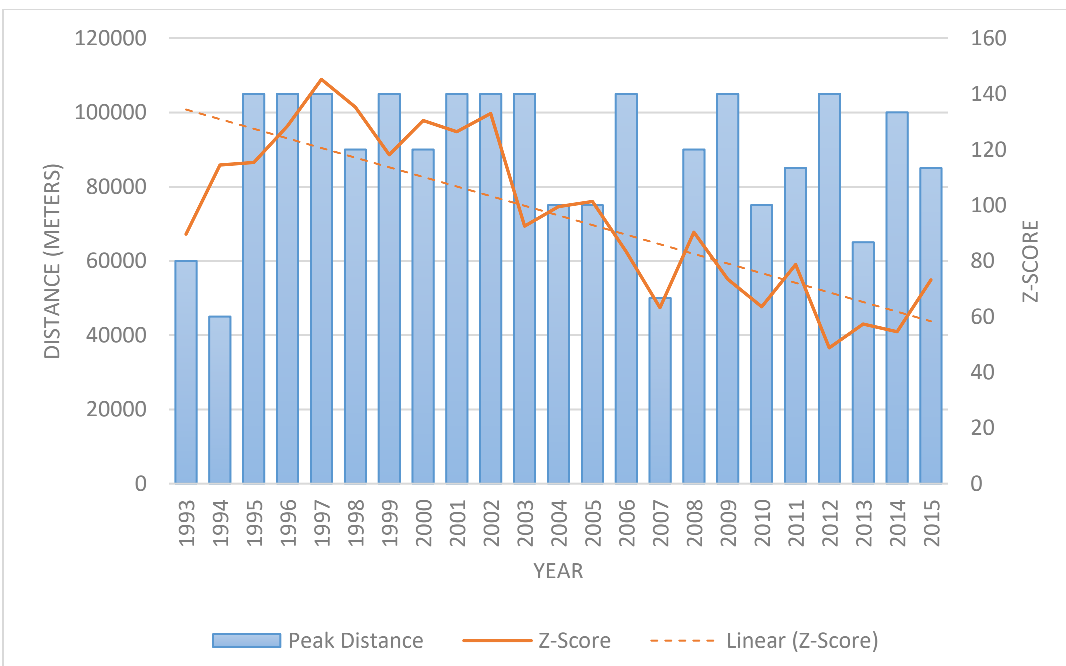

Figure 10. Peak z-score values for each year of Total Annual Number of Hauls and the distance band associated with the peak value

The trend line in both charts indicates that the peak z-score decreases over the study period. A decrease in the z-score values from 1993-2015 indicates that overall clustering is less pronounced towards the end of the study period in both number of hauls and total catch. Fluctuations in the distance band value did not have an overall trend for either dataset. The distance band for the hot spot and outlier analysis was chosen within the range of optimal values, but could not reflect the best distance band for all years.

4.2. Space-Time Cube

The aggregation of the original point datasets was completed using ArcGIS Pro 1.4.1. The resulting space-time bins contained 0-4 data points from the original NMFS observer data. Bins in active stacks with 0 data points were given an estimated value of 0. This resulted in the assignment of a 0 value to 11,184 bins out of a total of 17,595 bins, 64% of the total bins in the space-time cube. Figure 11 and Figure 12 show the two datasets in their three-dimensional form, with 23 time steps vertically stacked for each spatial location. The top layer shows data from the last time step, 2015. A small area of increased effort in the Aleutian Island chain is used in the inset to show the stacked data results and how they are visualized in the model. This completed space-time cube was used to obtain the results described in the rest of this chapter.

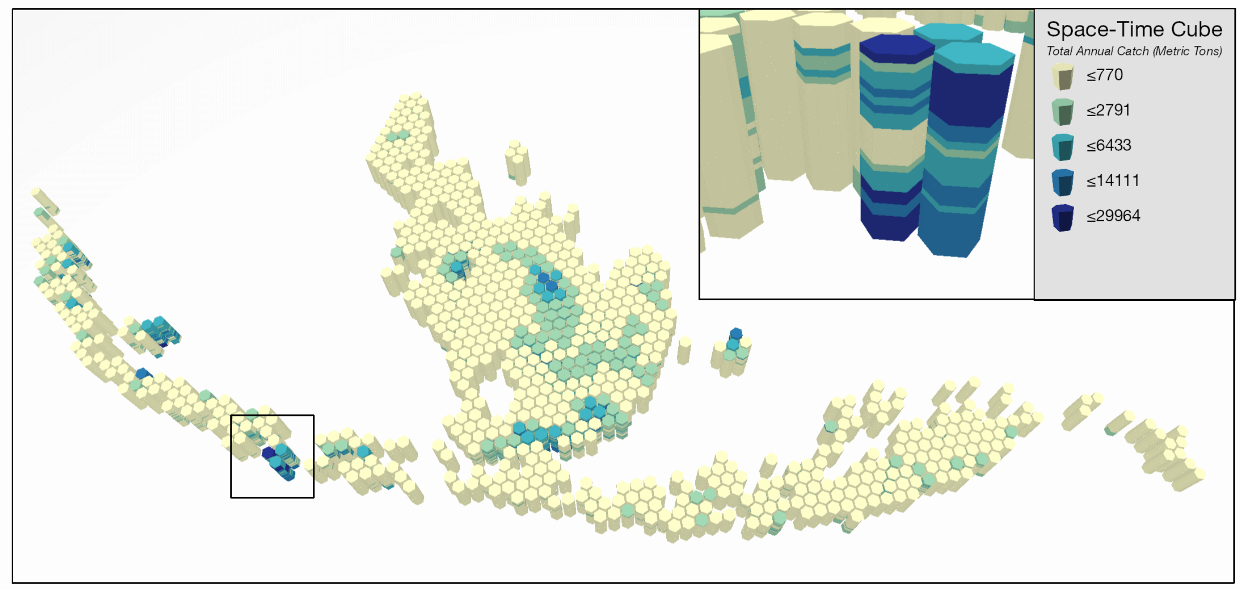

Figure 11. Space-time cube results for Total Annual Catch

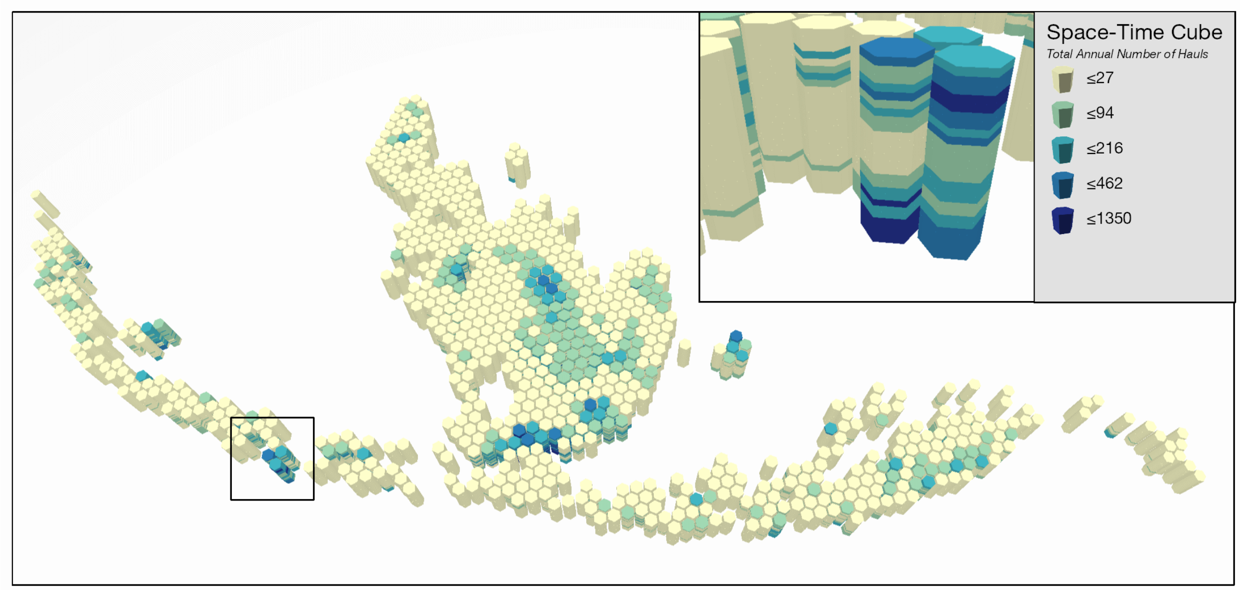

Figure 12. Space-time cube results for Total Annual Number of Hauls

4.3. Mann-Kendall Trend Test

The Mann-Kendall trend test results show the overall increase or decrease of the values in each bin. While the dataset as a whole showed no trend for total annual catch, and a slight downward trend for number of hauls, the results for individual locations show significant trends in both datasets. In the Total Annual Catch dataset, 263 locations show a significant downward trend, and 126 locations show a significant upward trend. For Total Annual Number of Hauls dataset, 346 locations show a significant downward trend, and 67 locations show a significant upward trend. The results of the Mann-Kendall trend test are shown in Figure 13 and Figure 14 along with all closure areas that were enacted before or during the study period. The comparison of the trend results provides insight on the bottom-trawl fleet's response to closure areas.

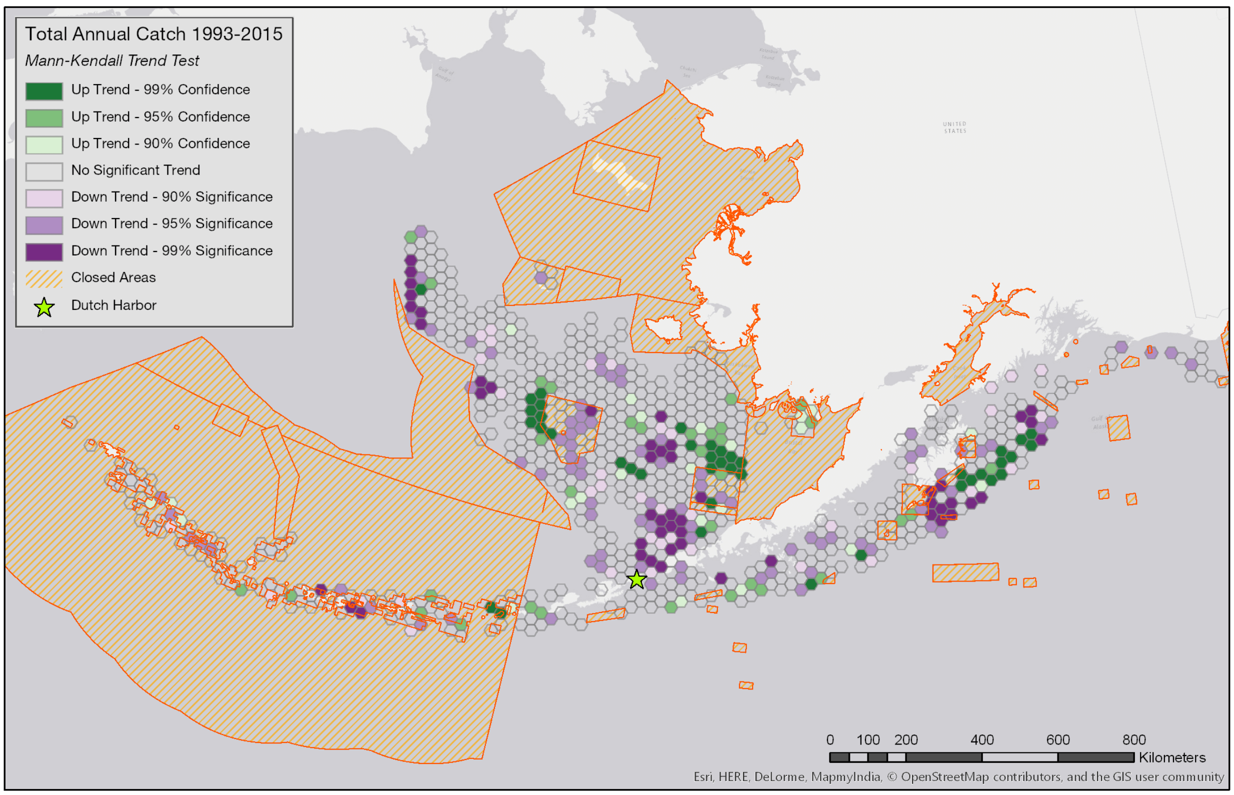

Figure 13. Results of the Mann-Kendall trend test for Total Annual Catch

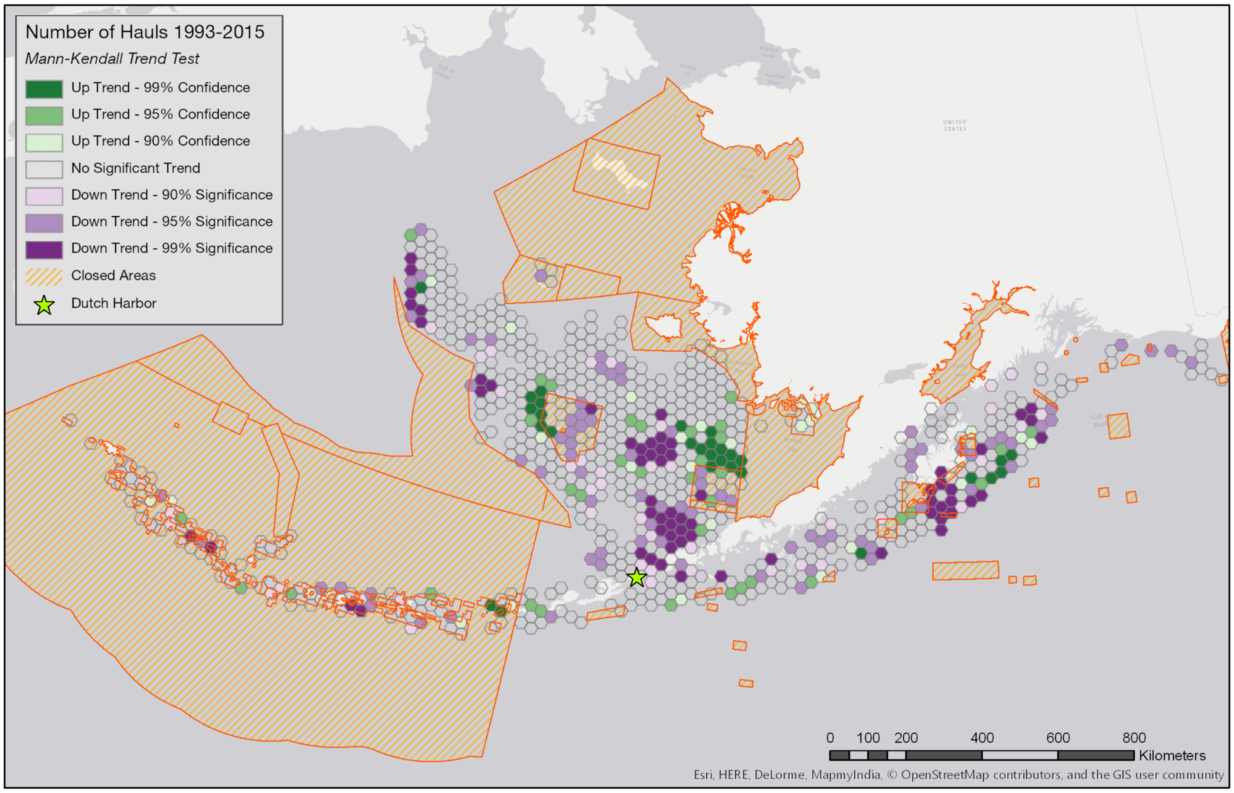

Figure 14. Results of the Mann-Kendall trend test for Total Annual Number of Hauls

The Pribilof Island Habitat Conservation Zone was closed to all bottom-trawl activity in 1995, the third time step into the study period. The area is shown in more detail in Figure 15. A significant downward trend is marked in areas that were previously fished. There is also a significant upward trend above the northwest boundary of the closure area. This may represent displacement of the fleet and a shift to new fishing territory.

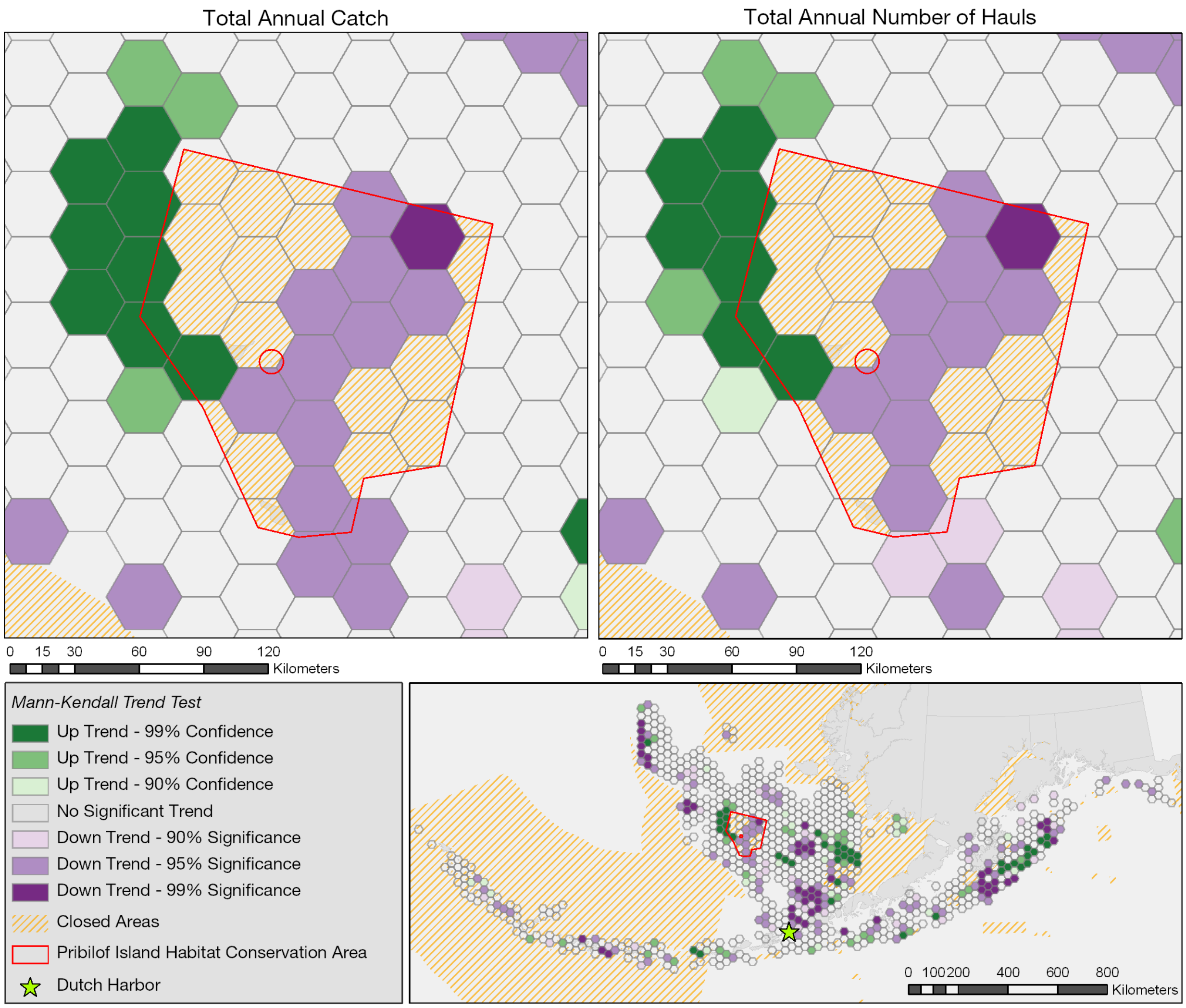

Figure 15. Pribilof Island Conservation Area enlarged for more detail

The Red King Crab Savings Area shows a similar pattern of displacement and shifting of fishing effort, which is shown in more detail in Figure 16. The Red King Crab Savings Area was closed year-round for bottom-trawl fishing in 1995, before which it was open seasonally (Witherell and Woodby 2005). The area shows a significant downward trend in the closed areas, and a significant area of upward trend locations just north of the boundary of the savings area.

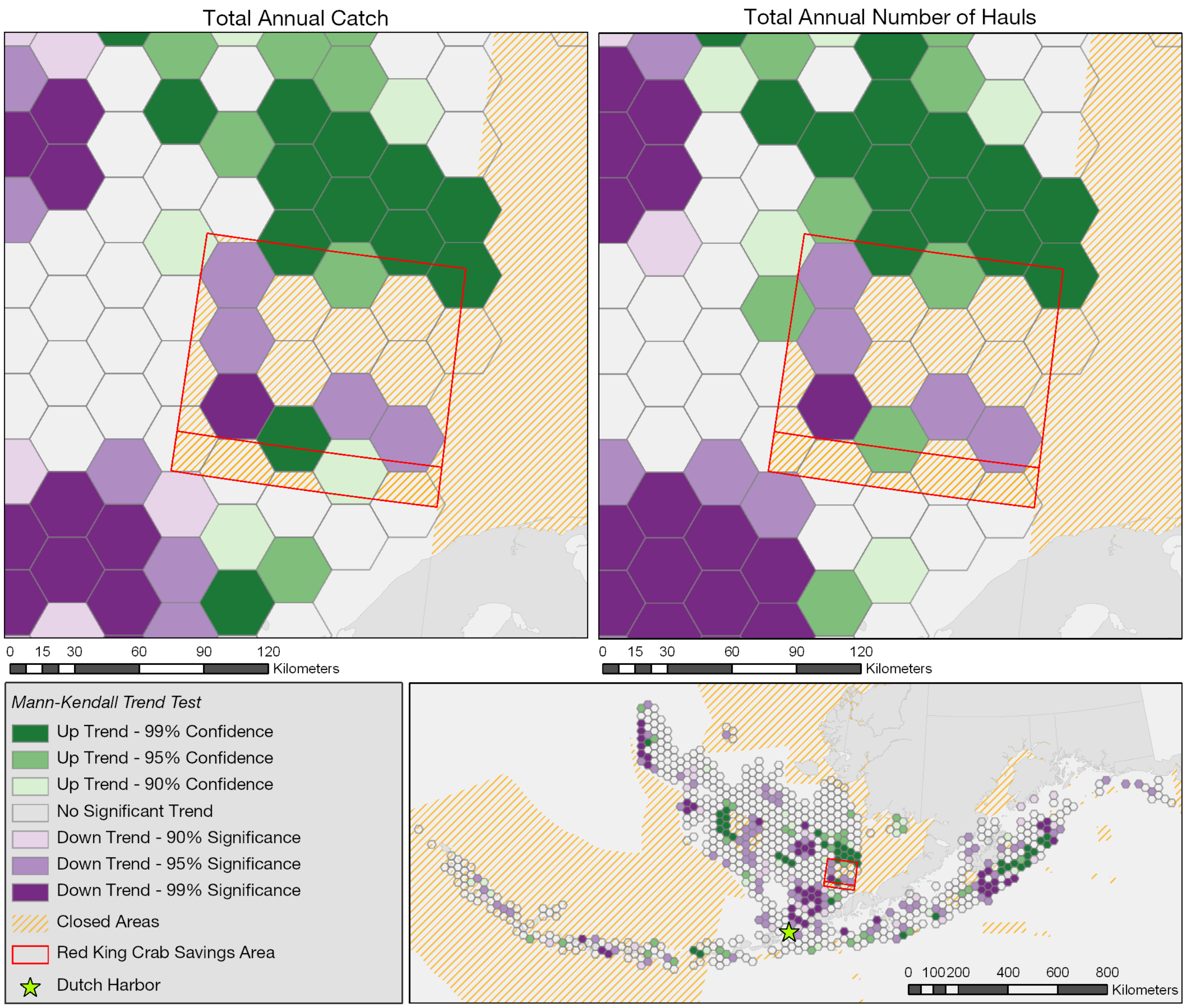

Figure 16. Red King Crab Savings Area enlarged for more detail

4.4. Hot Spot Analyses

Three versions of the hot spot analysis results are given in the following sections: cumulative z-scores, emerging hot spot analysis, and three-dimensional hot spots. The results of the space-time cube hot spot analysis gave corresponding z-scores to each bin that indicates the intensity of hot and cold clusters. Each cluster is an area that is significantly different from its surrounding neighbors. The hot spot results show areas that are more intensely fished than the surrounding neighborhood areas.

4.4.1. Cumulative z-scores

Cumulative z-score results show the areas that are most consistently associated with high or low clusters. Figure 17 and Figure 18 show the results for total annual catch and total number of hauls. Both maps indicate that large areas of the Bering Sea and Aleutian Islands are associated with consistently intense hot spots of fishing effort over the study period. Consistent usage could be associated with more chronic environmental impact. The area near the port of Dutch Harbor shows that it is more consistently used than other areas. The z-score intensity is higher in this area for number of hauls than total annual catch, which is indicative of the lower catch per unit effort (CPUE) capability of smaller vessels that must return to port more frequently. Nearshore Bristol Bay Trawl Subarea, located in the Southeastern corner of the Bering Sea region, also shows consistent hot spot association resulting from its special use status within a largely closed area. A small area at the eastern edge of the Aleutian Islands is consistently hot in both datasets.

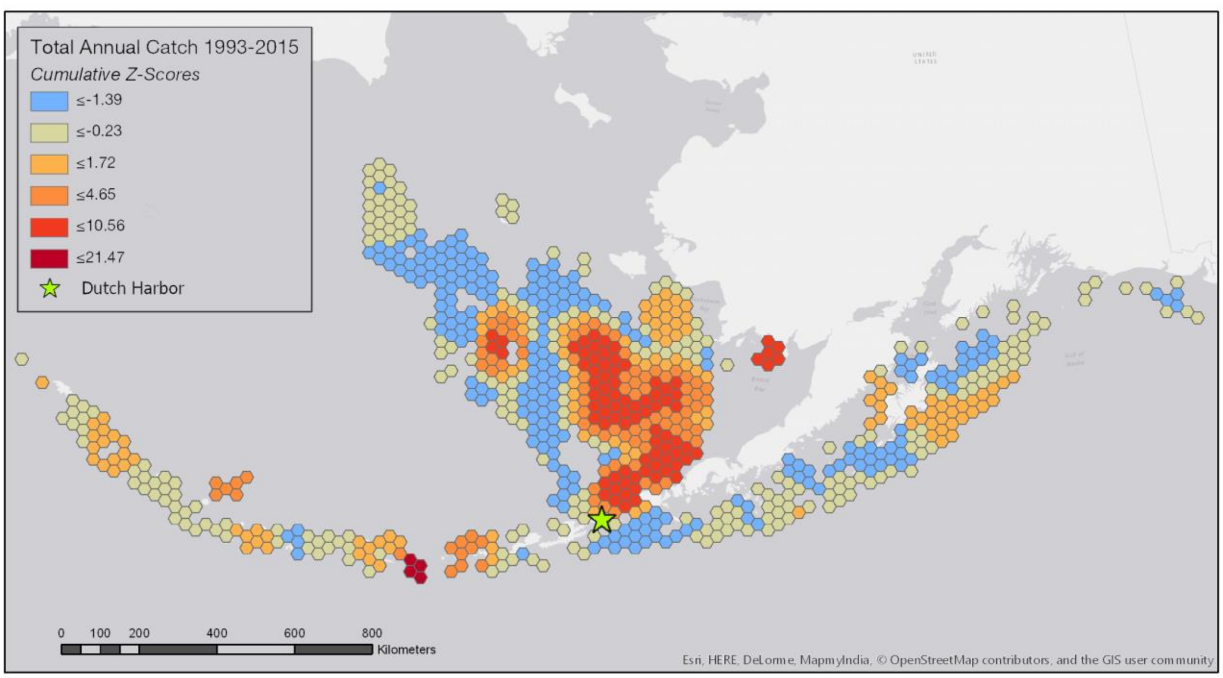

Figure 17. Cumulative z-scores from the hot spot analysis of Total Annual Catch

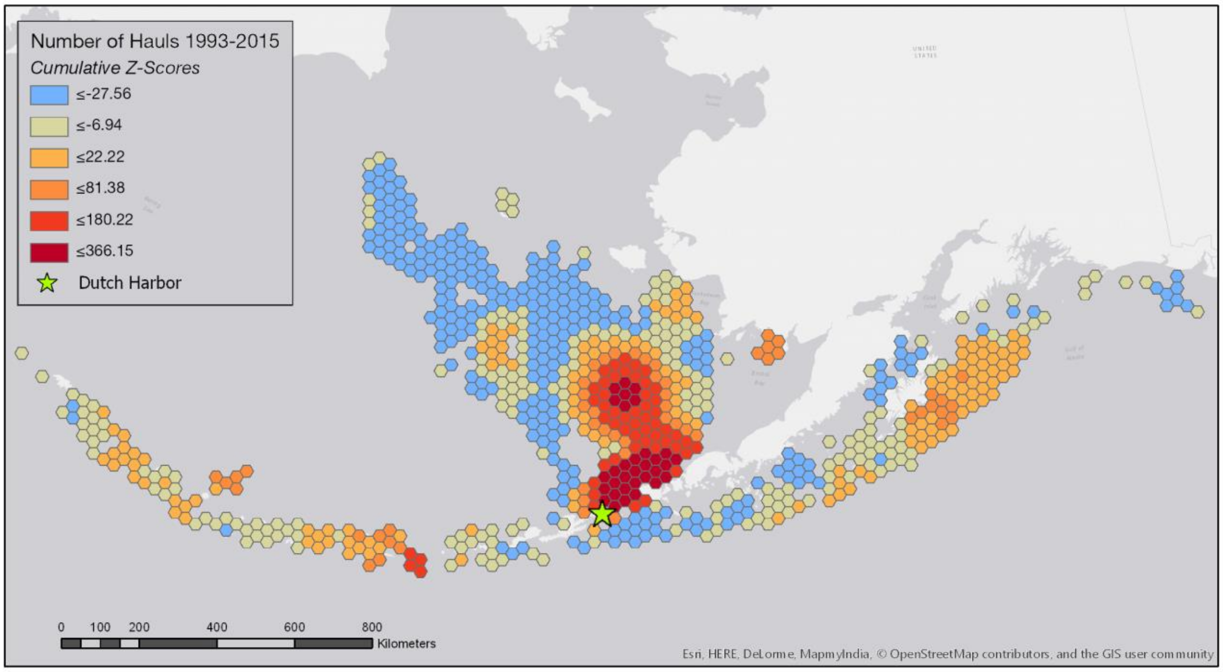

Figure 18. Cumulative z-scores from the hot spot analysis of Total Annual Number of Hauls

The cumulative z-score results ignore the fluctuations between individual years, and focus on the overall clustering intensity for all years within the study period. These results are beneficial to depict the most consistent hot spots, but the following emerging hot spot analysis and three-dimensional hot spots are better for showing year-to-year changes. The cumulative z-score analysis clearly identifies a “core” area for bottom-trawl fishing in the Bering Sea. It is marked by a large area with the highest cumulative z-score results (Port et al. 2016).

4.4.2. Emerging Hot Spot Analysis

The emerging hot spot analysis takes into account both consistency and intensity for each time step to determine a classification of the hot or cold spot. Time is a more important factor in this analysis than the simple cumulative z-score because each time step is assessed in relation to the others. Designation of the classifications is described in Table 3 in the methodology chapter. The results are shown in Figure 19 and Figure 20 below.

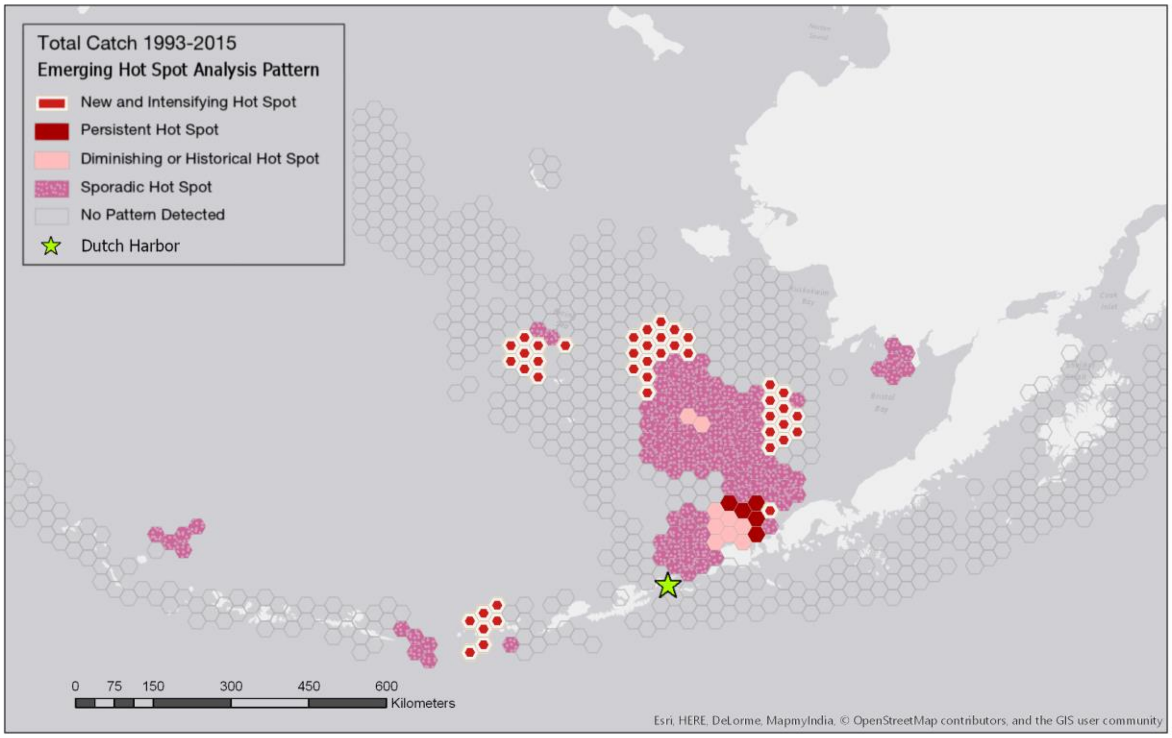

Figure 19. Emerging hot spot analysis results for Total Annual Catch

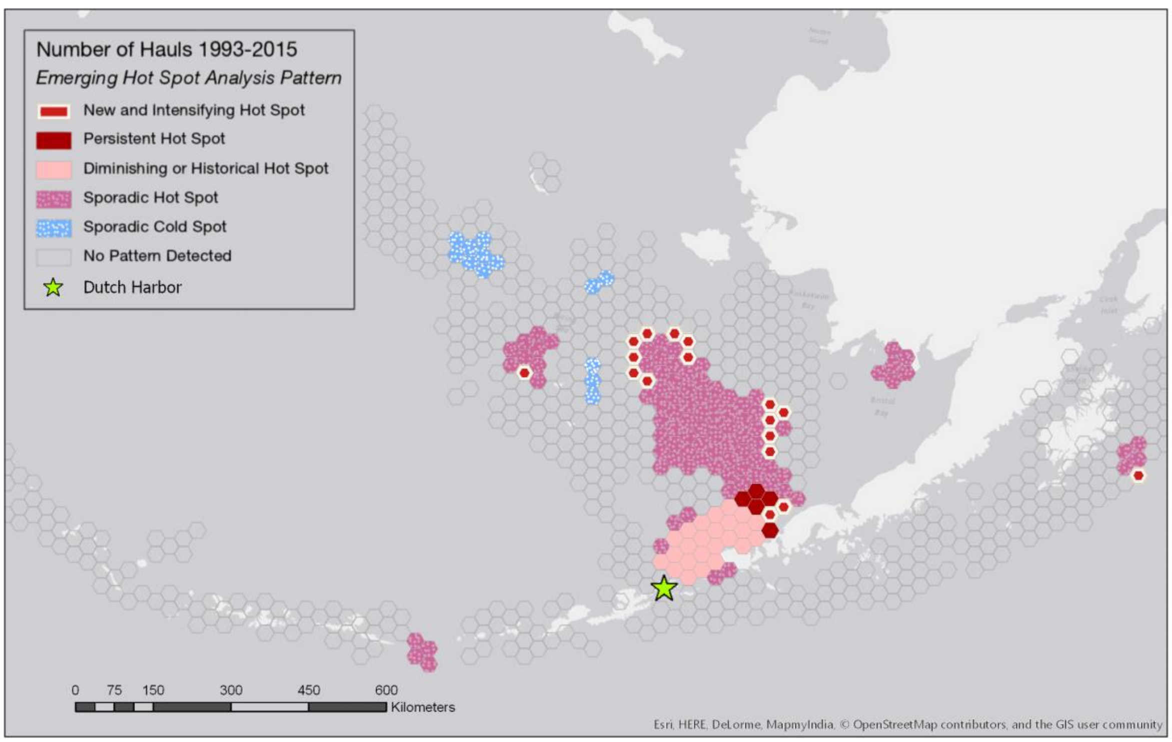

Figure 20. Emerging hot spot analysis results for Total Annual Number of Hauls

Results of the emerging hot spot analysis classify the area around Dutch Harbor as historic or diminishing. Although this area is consistently identified as a hot spot, its intensity has diminished over time. This gave additional information to the results of the cumulative z-score, which only showed it as consistently hot. There is still a clear core area in this analysis. Within the core area there have been sporadic lower values and only a small portion of the core has been persistently used over the 23-year period.

Both total catch and total number of hauls show that several areas have increased usage in the most recent time step. Many hexagons on the outer edges, particularly the southeastern edge and northern edge, of the identified hot spot region are classified as new or intensifying. This may indicate expansion into new areas or a shift in resource availability. Further analysis of these areas is described in Section 4.4.3.

4.4.3. Three-Dimensional Hot Spots

The three-dimensional hot spot analysis allows the entire stack of the space-time cube to be viewed. Areas that were marked new and intensifying in the emerging hot spot analysis can be examined through the complete annual range using this method. Figure 21 and Figure 22 show an enlarged view of the northern most area of the identified hot spot region. Most locations became a hot spot within the last three time steps and were only rarely hot spots in the earlier time steps. This provided verification that the change in fishing effort has intensified only in the most recent time steps of the study period.

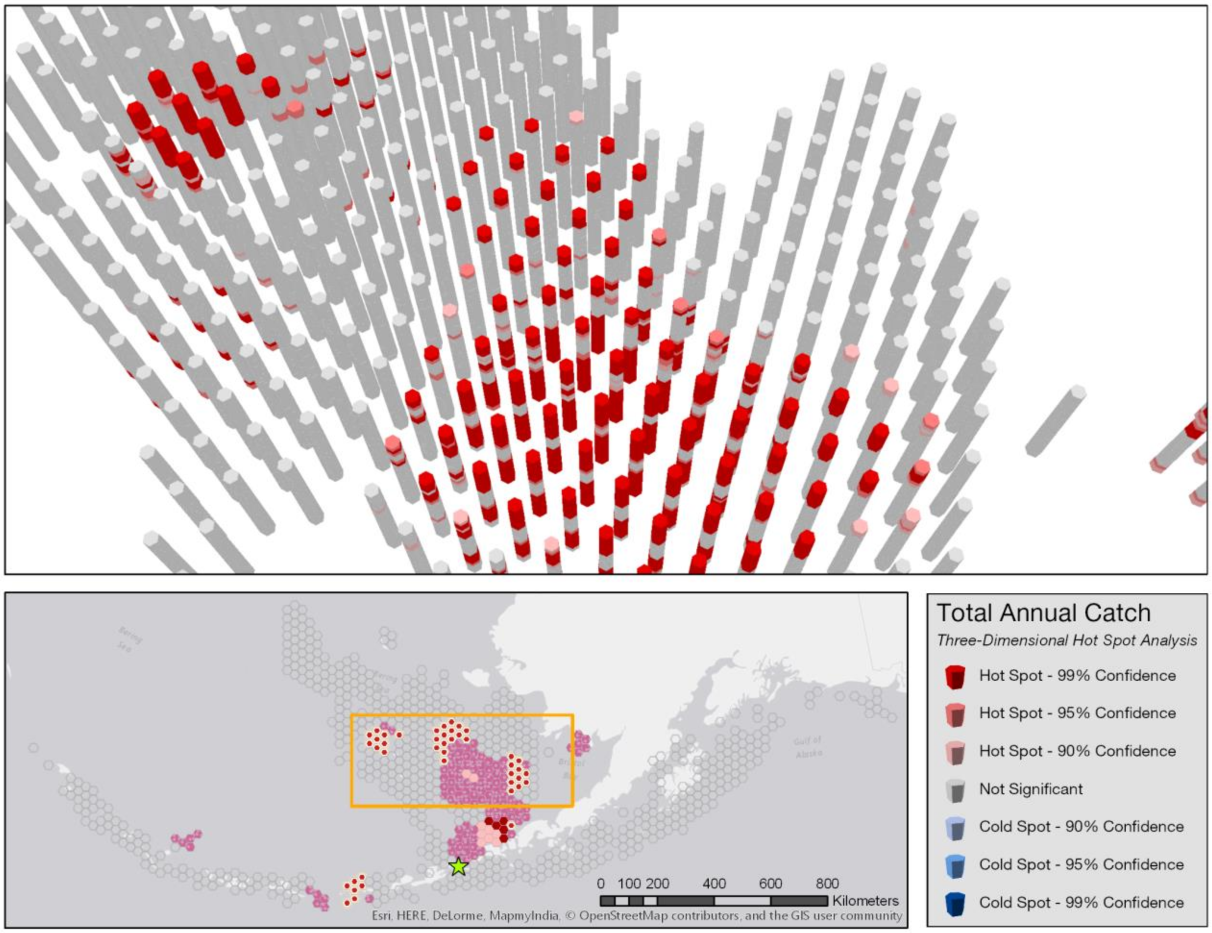

Figure 21. Three-dimensional hot spot analysis results for Total Annual Catch

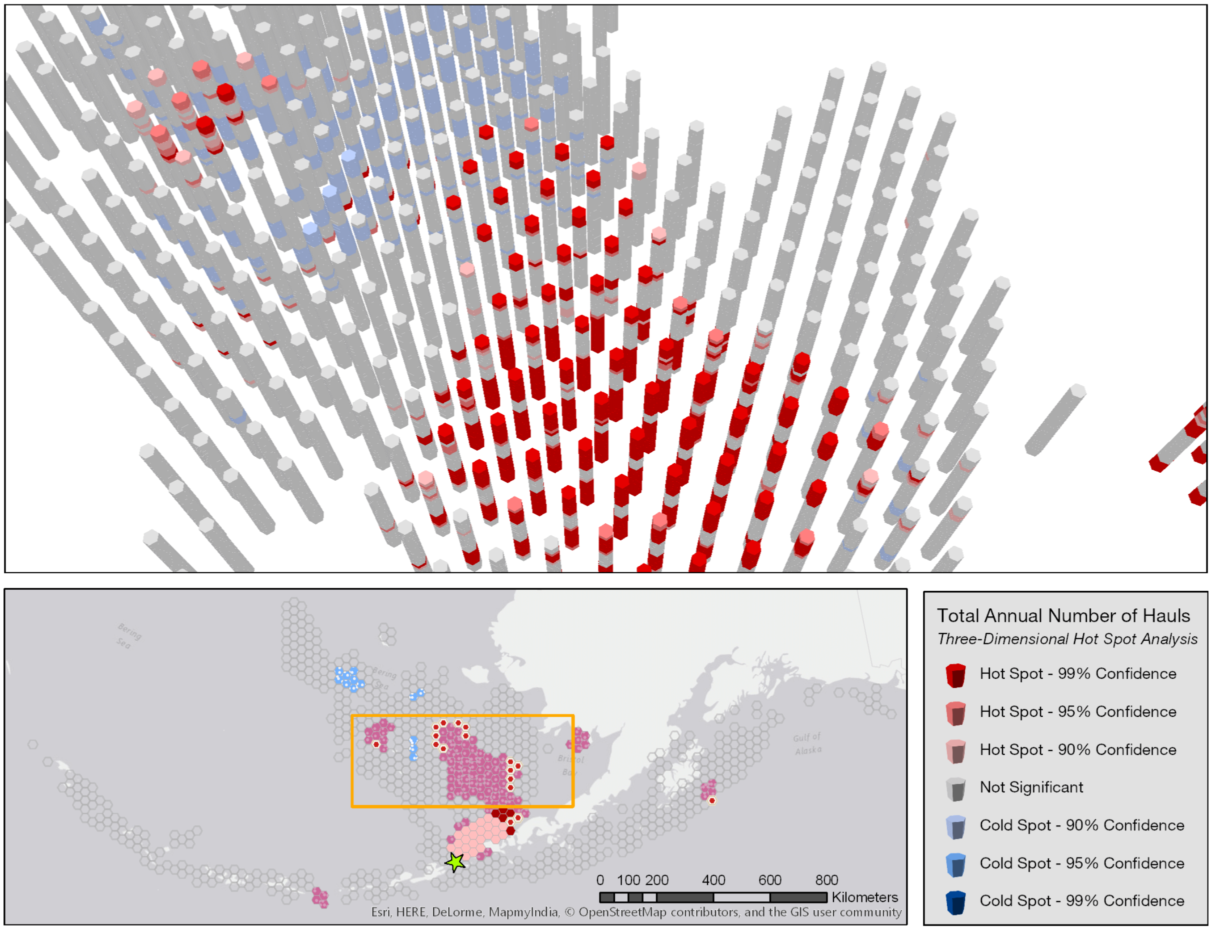

Figure 22. Three-dimensional hot spot analysis results for Total Annual Number of Hauls

The three-dimensional hot spot analysis also provided the necessary data to include in the time animations. Each time step can be separated and viewed year by year. The animation is described in further detail in Section 4.7.

4.5. Local Outlier Analysis

The local outlier analysis categorized cluster results into four categories: High-High, High-Low, Low-High, and Low-Low, which were described in the methodology chapter. At least one time-step for 319 of the 765 locations in the Total Annual Catch dataset was identified as an outlier category, High-Low or Low-High. In the Total Annual Number of Hauls dataset, 320 of the 765 locations had at least one time step identified as an outlier. Figure 23 and

Figure 24 show the classification of hexagons that were only one type of outlier for the entire study period. The rest of the hexagons were designated as multiple types.

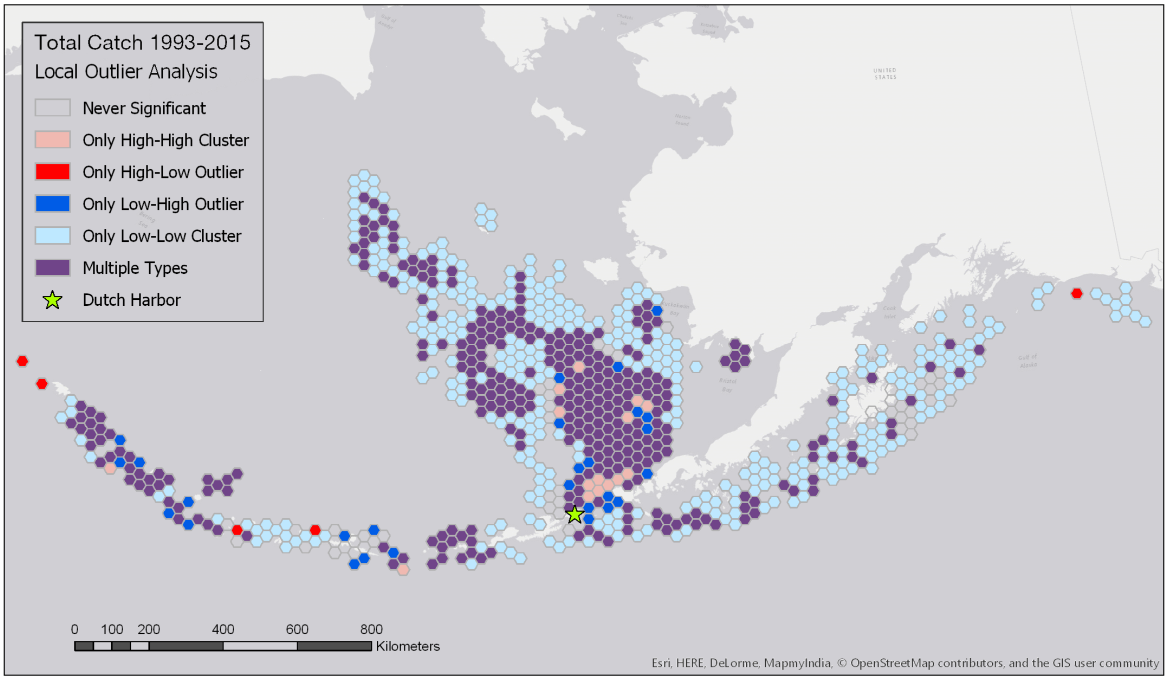

Figure 23. Results of the local outlier analysis for Total Annual Catch

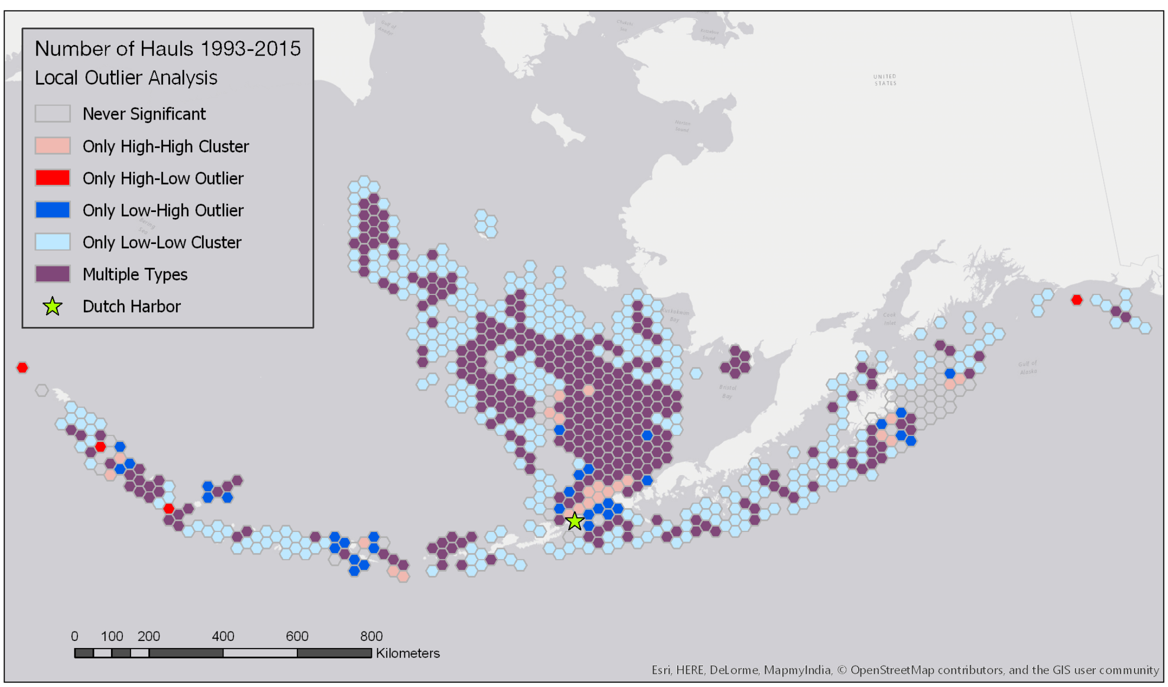

Figure 24. Results of the local outlier analysis for Total Annual Number of Hauls

The multiple types category encompassed the majority of locations and does not give much information about these areas. To better understand the outlier status of these locations, the three-dimensional view is needed. Figure 25 and Figure 26 are zoomed into a large area classified as multiple types to view the details of each year for total annual catch and total annual number of hauls. The area shown is mostly identified as High-High clusters with some areas identified as Low-High outliers. The outlier space-time bins represent areas that do not fit with the overall pattern of the large hot spot region. For the total annual catch dataset, 912 or 5.4% of the space-time bin values were categorized as Low-High outliers, and 200 or 1.2% were categorized as High-Low outliers. For the total annual number of hauls data, 760 or 4.5% of the space-time bin values were categorized as Low-High outliers, and 238 or 1.4% were categorized as High-Low outliers.

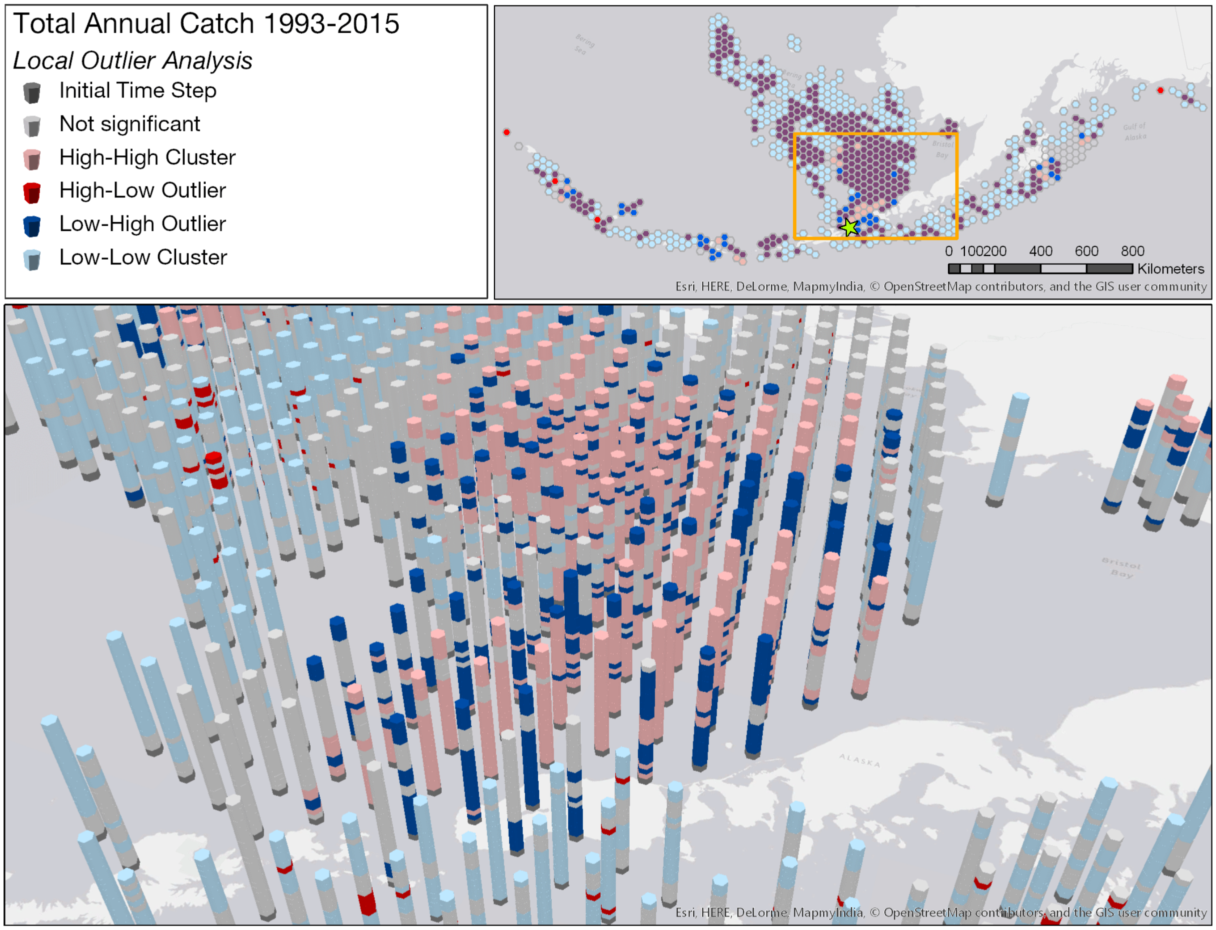

Figure 25. Three-dimensional view of area identified as Multiple Types in Total Annual Catch

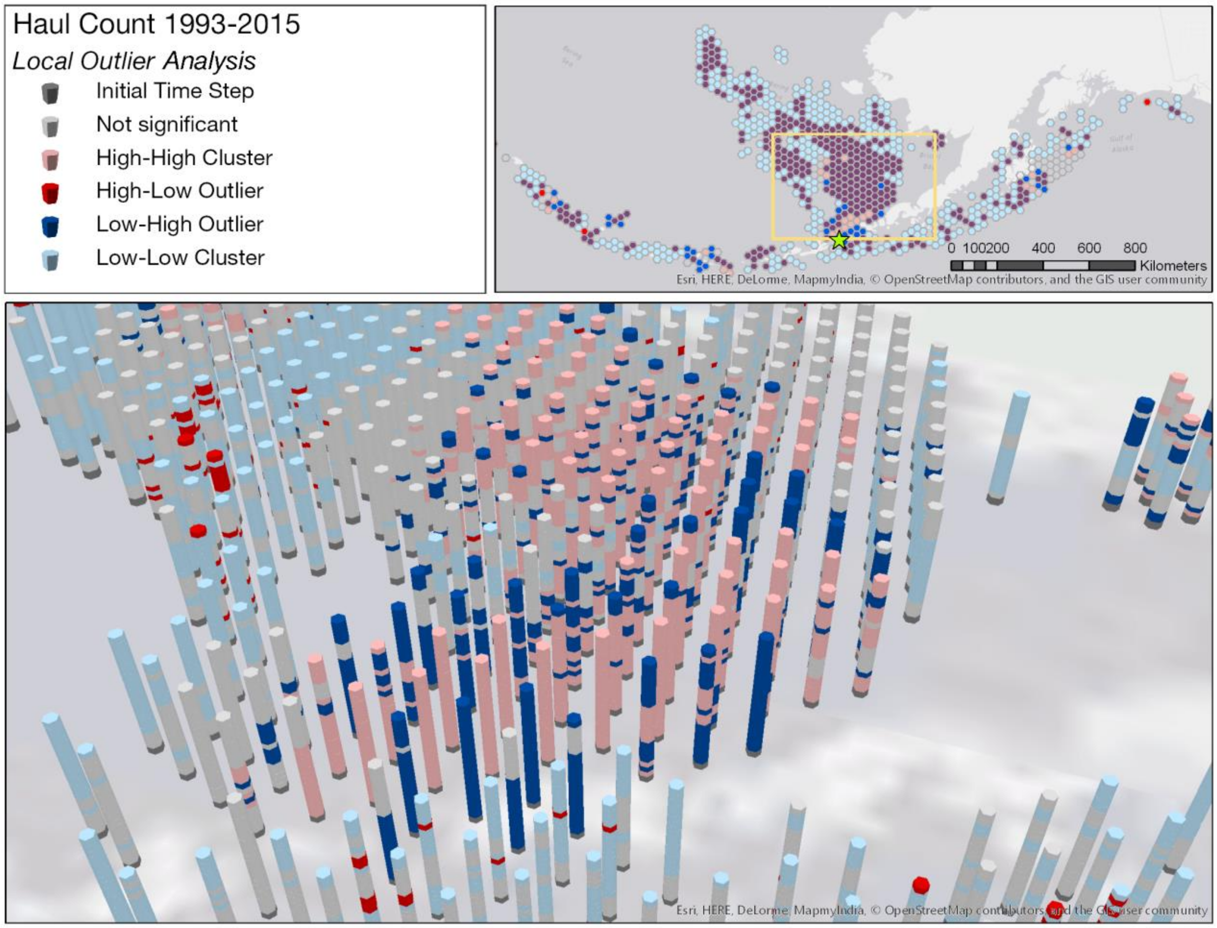

Figure 26. Three-dimensional view of area identified as Multiple Types in Total Annual Number of Hauls

4.6. Sea Ice Concentration Results

The sea ice concentration data were classified into different levels of ice effect for analysis in combination with the catch and haul fishery data. First, low and high ice effect years were designated to evaluate the differences in average total catch and average number of hauls. The ice effect level was determined for each space-time cube location to compare the data by spatial location. Finally, isolines of ice concentration data were created to use as guidelines in the animations described in Section 4.7.

4.6.1. Low Ice Effect and High Ice Effect Years

The average value for the study area ice effect was compared for each year of the time period to determine lower than average and higher than average ice effect years. Figure 27 shows chart results of this analysis with the vertical axis divided into 0.5 standard deviations from the median value of 23.14 days per year. The years designated as below average ice effect years were 1993, 1996, 2001-2005, and 2014-2015. Average ice effect years were 1997-1998, 2000, 2006-2007, and 2011. The years designated as above average ice effect years were 1994-1995, 1999, 2008-2010, and 2012-2013.

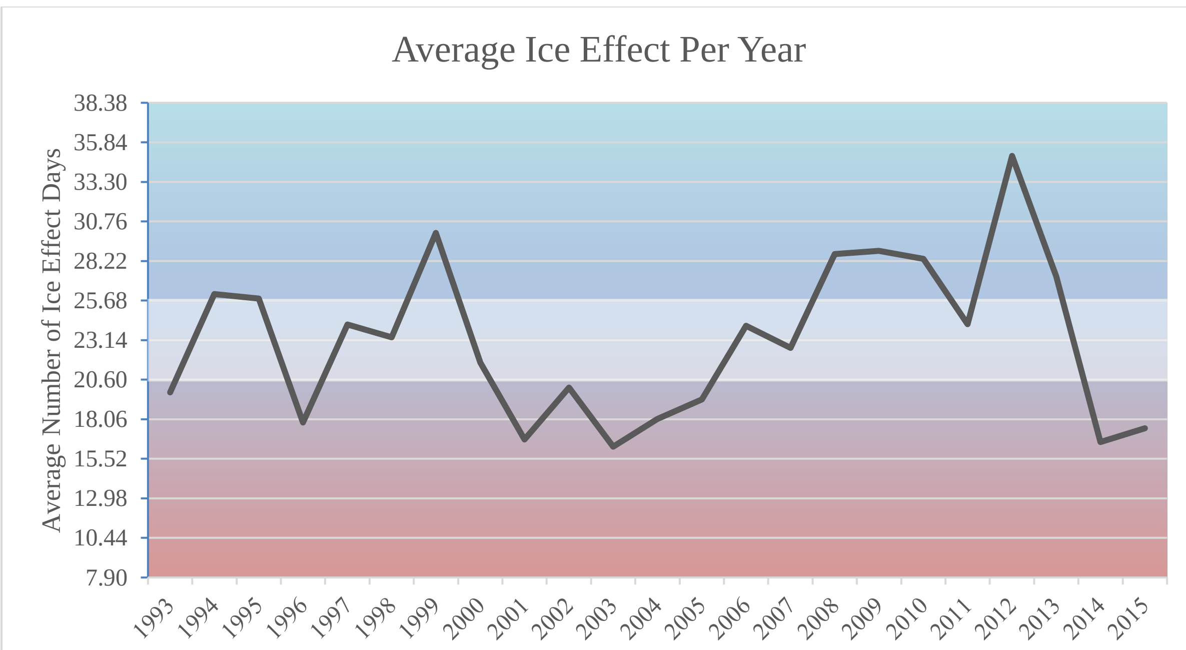

Figure 27. Average number of ice effect days per year with 0.5 standard deviations marked

4.6.2. Average Sea Ice Days and Classification

The Sea Ice Concentration dataset was divided into effect areas by the number of days per year that the area had a 20% or greater sea ice concentration level. The space-time hexagons were used to match the fishery data for comparison. The average values of number of days effected by ice for each hexagon is shown in Figure 28. The area is separated into five categories of ice effect from No Effect, an average of less than one day per year, to the Maximum Effect 150 days per year or greater of sea ice effect. Sea ice only affects the Bering Sea fishing area, with the Aleutian Islands and Gulf of Alaska showing no days affected by sea ice. Areas without hexagons have no sea ice concentration data, most of which coincide with large islands, where sea ice concentration data would not be applicable.

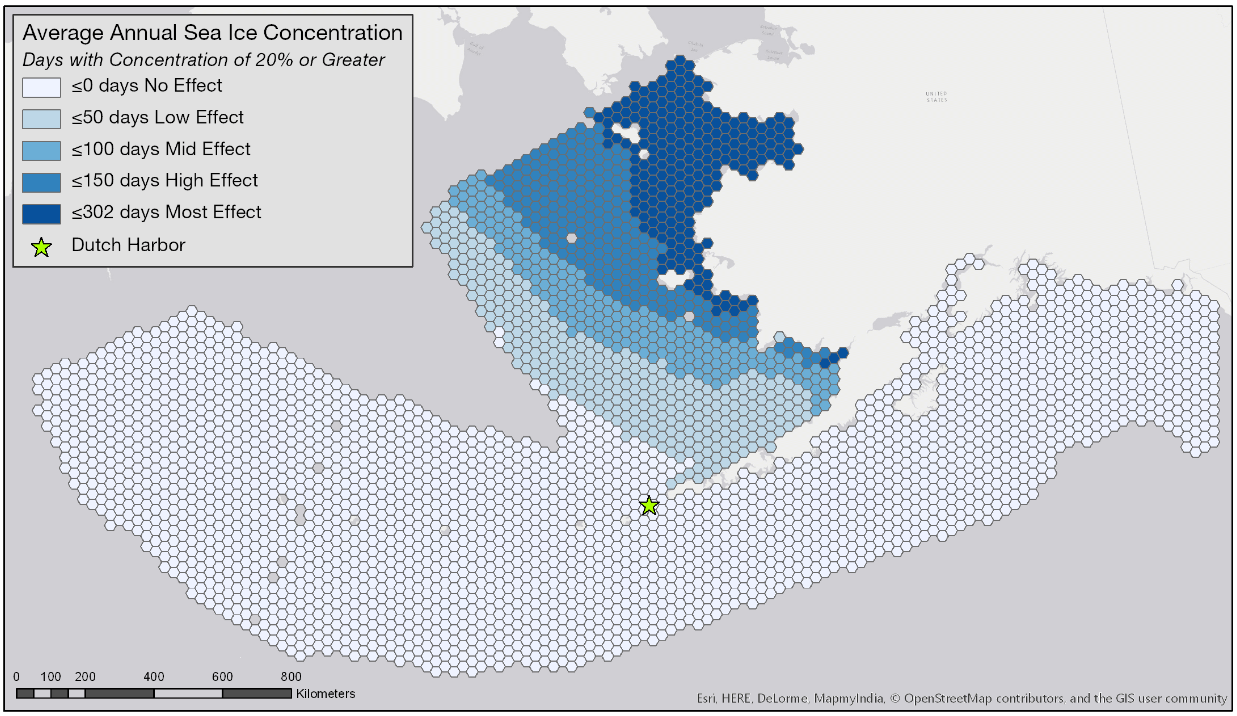

Figure 28. Average number of sea ice effect days per year for each location bin in the space-time cube

4.6.3. Average Fishing Effort and Ice Effect Areas

To show changes in bottom-trawl activity, fishing effort data were summarized for low ice effect years and high ice effect years. The average number of hauls for each hexagon for all years designated as high ice effect years, eight years in total, and an average number of hauls for each hexagon for all years designated as low ice effect years, nine years in total, are shown in Figure 29. Average annual number of hauls for high ice effect and low ice effect years are shown in Figure 30. The figures only show hexagons within the Bering Sea management area. The

Aleutian Islands and Gulf of Alaska do not have seasonal sea ice accumulation. The zones of sea ice effect are outlined from the average effect hexagons shown in Figure 28.

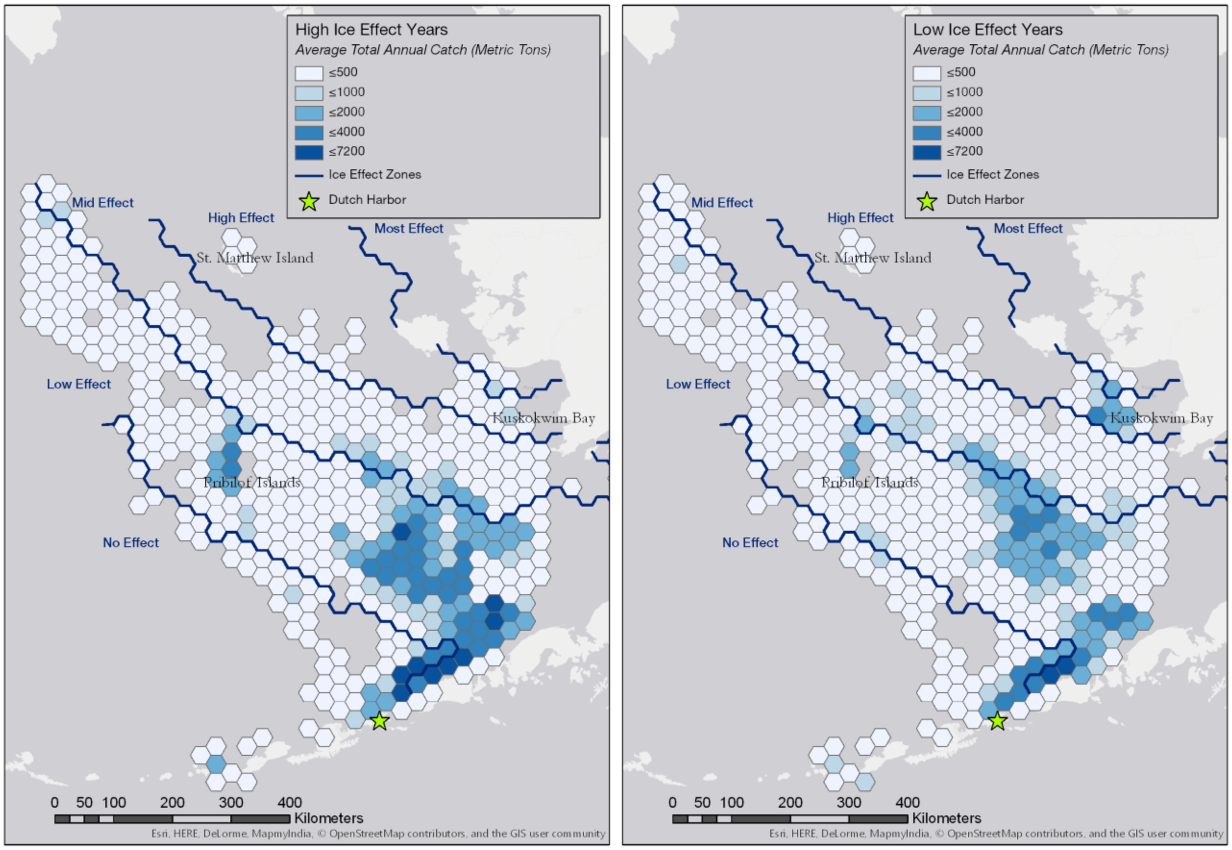

Figure 29. Average Total Annual Catch for high ice effect years and low ice effect years

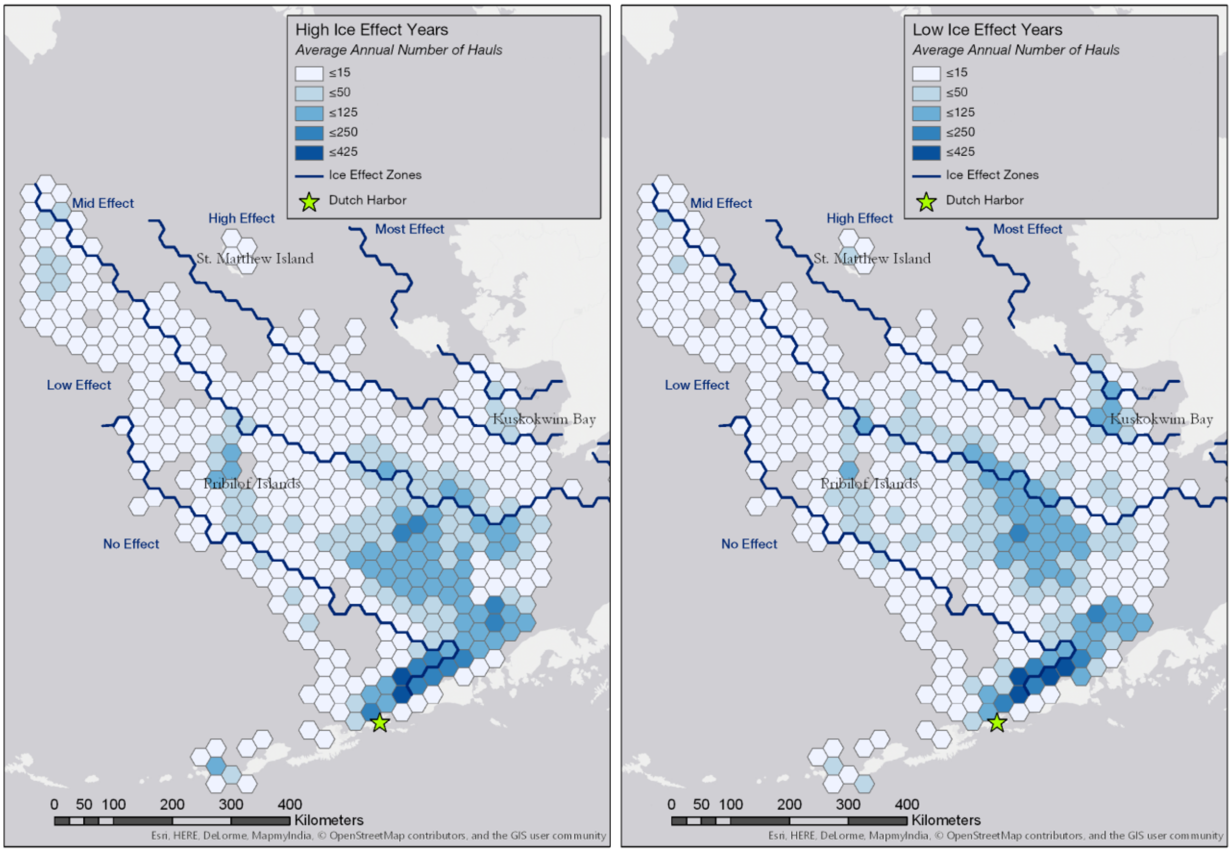

Figure 30. Average Total Annual Number of Hauls for high ice effect years and low ice effect years

The presence of sea ice has a noticeable effect on the spatial distribution of fishing effort in all areas of the Bering Sea. Low Ice Effect years show a higher average activity in areas designated as mid effect and high effect zones for average sea ice concentration. This is shown in both the average total annual catch and the average total annual number of hauls, particularly in the area just outside Kuskokwim Bay and the area north of the Pribilof Islands. In addition, areas with no sea ice days have decreased average activity during low ice effect years for both datasets.

4.6.4. Isolines

Average isolines allow for improved visual analysis of movement from one area of ice effect to the next. They provide guidelines for the eye to better follow the effect of sea ice on the total annual catch and total annual number of hauls datasets. The isolines were created to mark average sea ice effect days with 50 day increments. The resulting lines are used within the two animations of yearly ice effect and yearly fishing effort described in Section 4.7.

4.7. Animations

Visual pattern recognition is a powerful analytical tool. Two animations were created to visually compare sea ice concentration and fishing effort hot spots. Each animation contains the yearly sea ice effect raster dataset, the isolines showing the average ice effect for all years, and closed areas for the active years. The first animation contains the hot spot results of the total annual catch data from the space-time cube three-dimensional analysis. The second animation contains the hot spot results of the total annual catch data from the space-time cube three-dimensional analysis.

4.7.1. Total Annual Hauls Hot Spot Animation

The thumbnail frames for the completed total annual hauls animation are included in the Appendix A, along with a digital appendix of the MP4 animation file. Each frame represents one year of the sea ice days raster and one year of the total annual hauls hot spot results. The isolines represent the average for the entire study period.

The hot spot results show a great deal of movement and variation from year to year with the most consistently hot area being near the port of Dutch Harbor. Hot spots seem to grow and recede again and reach their largest range in the last two frames of the animation. No cold spots exist in the total annual catch results. It was not possible to see a visual connection between the movement and growth of hot spots and the sea ice effect levels.

4.7.2. Total Annual Number of Hauls Hot Spot Animation

The completed animation and thumbnail frames for the total annual number of hauls are located in Appendix B. As described in the first animation, each frame represents one year of the sea ice days raster and one year of the total annual hauls hot spot results. The isolines represent the sea ice average for the entire study period.

The annual number of hauls hot spot results show similar patterns of movement and growth as the total annual catch dataset. The most consistently hot area is near the port of Dutch Harbor, and the largest extent of the hot spot area occurs in the last two frames. No visible pattern between number of hauls and sea ice concentration data was detected.

Chapter 5 Discussion and Conclusion

A space-time cube analysis was used to study the spatiotemporal footprint of bottom-trawling in the Bering Sea, Aleutian Islands, and Gulf of Alaska. The study asked several research questions which were of interest not only for the topic itself, but also for determining if the space-time cube was a viable research tool for answering these types of questions. The first question asked if Alaskan bottom-trawl fishing effort occurs in non-random spatial clusters. The second and third questions ask if the spatial extent and intensity of Alaskan bottom-trawl fishing effort has changed or expanded over time. The fourth and fifth questions ask how MPA closures and changing seasonal sea ice conditions have affected the spatial distribution of Alaskan bottom-trawl fishing effort over the study period. The final question asks if the space-time cube is an effective tool for analyzing Alaskan bottom-trawl fishing effort, which is addressed within each topic and in the Conclusions Section. A discussion of each research topic describes the strength of results found and areas that could be improved in future research.

5.1. Non-Random Clusters

Fishing effort occurs in non-random clusters and is not homogenous over space and time. This result was the expected result and followed the framework of several studies that have also concluded that fishing effort, bycatch, and resource availability all show significant non-random clustering of values (Jalali et al. 2015; Lewison et al. 2009). The underlying causes of this clustering can be a complex interaction of many factors including, but not limited to, underlying bathymetry, clustering and schooling behavior of target species, fleet prior knowledge and sharing of information, regulatory parameters, weather conditions, and traveling costs.

Aggregation of the original AFSC dataset may reduce the efficacy of this tool if spatial autocorrelation was greater at a smaller scale than the 400 km^2 grid. Despite this limitation, a range of peak spatial autocorrelation was found between 45,000 meters and 105,000 meters, after which increased distances reduced spatial autocorrelation. This indicates the necessity of localized studies of fishing effort rather than summarizing by broader NMFS reporting areas or Alaska Department of Fish & Game Statistical Areas, which are commonly used by fishery management entities.

The Moran's I statistic was difficult to apply to the temporal aspect of this project. Individual years were used for the analysis rather than being able to include neighbors in both time and space. A more time aware spatial autocorrelation toolset would improve the results of this analysis and may have pinpointed the optimized scale for the dataset as a whole. Space-time cubes may be a good foundation on which to advance spatiotemporal clustering analysis.

The spatial autocorrelation test also revealed an overall trend of decreasing z-score values in both the total annual catch and number of hauls datasets. This suggests that fishing activity has not intensified over time globally, but does not rule out the possibility of localized intensification in certain areas. This phenomenon was further analyzed using the hot spot analysis. Reduced clustering intensity may be the result of less vessels participating in the bottom-trawl fishery, which has declined greatly since the early 1990s due to limited entry and a moratorium on new permits (NPFMC 2016).

5.2. Expansion of Fishing Areas

The cumulative z-score and emerging hot spot analyses identified a common core area that encompasses the most utilized area for the bottom-trawl fishing fleet in the Bering Sea. Patterns in the emerging hot spot analysis show that both total annual catch and total number of hauls are increasing in intensity in marginal areas surrounding the core nucleus of fishing activity. This indicates possible expansion into previously less-utilized regions, but not outside of the total spatial extent of typical fishing activity. The Gulf of Alaska and Aleutian Islands did not show a clear nucleus of fishing effort and only sporadic hot spot areas were identified. The expansion of the bottom-trawl fishery in those areas is inconclusive from this study.

Moving into marginal areas is an environmental concern for several reasons. The move could indicate that resources are no longer as abundantly available in the core area, particularly, the area nearest Dutch Harbor, which is more likely to be over-utilized due to its proximity and easy access to all types of vessel activity (Stewart et al. 2010). This type of expansion was also discovered in the spatial history of the groundfish fishery in California, which showed that more accessible areas were fished first, with more distant locations peaking at later dates in the study period (Miller et al. 2014). Determining if resource depletion has occurred in the Bering Sea bottom-trawl fishery would require further study of the area.

The expansion of bottom-trawling is also a concern for benthic habitats. Marginal areas are more susceptible to disturbance and areas that are not normally fished may be newly exposed to fishing pressure (Kaiser et al. 2016). Preventing expansion of the spatial footprint of bottom-trawl fishing would greatly reduce the environmental impact caused by fleet activity in marginal areas (Jennings and Lee 2012). Using aggregated data does not accurately show the areas that are used within each cell. The hauls may have occurred in a relatively small portion of each cell, which is consistent with the clustering of fleet activity. Further analysis, with a higher resolution dataset would be needed to understand fishing expansion into new or marginal territories. Understanding the motivation and underlying causes of fishing effort expansion would greatly improve the resiliency of this fishery.

5.3. Effect of Closure Areas

Marine Protected Areas (MPA) affect the amount of area available for use by the bottom-trawl fleet. Many areas are closed year-round or seasonally to protect benthic level species. It was hypothesized that the introduction of new MPAs would act to concentrate the fleet into smaller areas or cause the fleet to expand into new areas. MPAs have become key components in the conservation of biodiversity and important habitat areas, however, there are also many shortcomings to MPAs, especially if they are poorly planned. Shifts in fishing behavior may indicate a failure to prevent the degradation of the ecosystem surrounding the MPA or an unintended negative consequence of the MPA (Agardy, di Sciara, and Christie 2011).

The Mann-Kendall trend test on the space-time cube provided evidence for the overall change of total catch and number of hauls over the course of the entire study period. This is a simple measure of an overall upward or downward trend in fishing effort in and around the vicinity of a protected area. The results of the hot spot and closed area animation were also examined for evidence of the effect of closed areas on a year-by-year basis. The animation indicates how immediate the changes were and if the changes were significant enough to create a hot or cold spot in the area.

The results of the Mann-Kendall trend analysis showed a pattern of displacement and relocation of fishing effort near two MPAs: Pribilof Island Habitat Conservation Area and Red King Crab Savings Area. Both areas contained a significant downward trend in total annual catch and total annual haul within the boundaries of the closed areas. This shows that the areas were being actively fished prior to the enactment of the closure. In addition, significant upward trends are located just outside the boundary area, possibly representing a shift in effort to the nearest available open area. This is consistent with the hypothesis that closure areas would cause the expansion of fleet effort into previously less used areas that remained open. The Mann-Kendall trend test of the space time cube was successful in revealing the movement of effort caused by closed areas.

The results of the hot spot analysis compared with the closure areas have a less obvious connection. The Pribilof Island Habitat Conservation Area was part of a hot spot cluster for the two years prior to the enactment of the closure. Following the enactment, there are some areas with a 90% probability of being a hot spot. This is likely the result of using prior year spatiotemporal neighbors in the analysis. After this, the area is either not significant or part of a 90% probability cold spot. The area above the boundary does not appear as a hot spot cluster until 2005 in the total annual catch hot spot results and 2008 in the total annual hauls dataset. This suggests that the shift in effort to the outside boundary areas may not have immediately followed the closure of the Pribilof Island Habitat Conservation Area.

The second MPA, the Red King Crab Savings Area, gives results that are impossible to determine any pattern of hot spot relocation. The area is very near the largest hot spot region and any results appear to be overtaken by its effects. A finer scale analysis may have been able to better detect displacement or the area surrounding the closure was already significantly used and did not show increased intensity in the hot spot analysis.

The majority of closed areas show no pattern of displacement and shifting of fishing effort in either the Mann-Kendall Trend test or the hot spot analysis animation. For many closure areas, this was the expected result. Particularly, in 2006, closure areas were placed in all areas that were historically unused by the bottom-trawl fleet. This increased the area protected from high disturbance fishing without having any impact on the fleet’s ability to fish. The lack of results for other areas may be a result of little historical usage or the need for a finer resolution test.

5.4. Effect of Seasonal Sea Ice Concentration

The creation of a compatible sea ice dataset was the first step in determining its effect. The number of days per year of sea ice concentration greater than 20% was chosen to represent the amount of time the fishing grounds were unavailable for use. The presence of sea ice is not a hard boundary for fishing vessels, which may choose to enter ice areas despite increased danger and difficulties. The resulting dataset was used to determine years of higher than average ice effect and lower than average ice effect. Using the average for all NMFS reporting areas provided a reduction in the number of non-fishing ground points included in the dataset. However, it may have been beneficial to reduce the analysis boundary to include only areas that were used by the bottom-trawl fishing fleet. Using the larger area average caused some years to be selected as high ice effect years, when very little of the fishing area was affected by the increased ice amounts in the northern most section of the NMFS reporting areas.

Despite the possible misidentification of high ice effect years, there were distinct differences in the spatial distribution of the average number of hauls and catch for high ice effect years and low ice effect years. Low ice effect years show increased annual catch and number of hauls in the area just outside of Kuskokwim Bay and the area north of the Pribilof Islands. These areas average 100-150 days of sea ice effect. These areas would likely see increased usage as the number of low ice effect years increases due to global warming. This portion of the analysis was successful in identifying two areas that show evidence of bottom-trawl fishing increasing in high ice areas when they are more available. The extent to which activity would increase is not apparent from these results. The study completed by Pfeiffer and Haynie (2012) on the Bering

Sea Pollock fishery found that some years show a change in effort from warm to cold years, but the overall effect is small, and the fleet is more driven by other factors.

The time animation of hot spot analysis results and sea ice concentration effect were also used to visually identify changes in fishing effort due to presence or absence of sea ice. The two datasets did not appear to show any connection between the movement of sea ice extent and the location of hot spots. Very few hot spots appear in areas that average more than 100 days of sea ice concentration until the final three time steps, 2013-2015. Both 2014 and 2015 were low ice effect years, but the pattern does not appear in any other portion of the dataset. This seems to confirm the assertion of Pfeiffer and Haynie (2012) that sea ice concentration has little effect on the spatial distribution of fishing effort. If some vessels moved into new areas, it was not enough effort to create a significant hot spot. Although the animation did not detect any spatial pattern connection between sea ice concentration and fishing effort hot spots, the space time cube provided the needed tools to reject this hypothesis.

5.5. Conclusions

Bottom-trawl fishing continues to be a topic of controversy because it directly interacts with the benthic layer. The goals of this study were to better understand the spatial extent of the bottom-trawl fishery in Alaska and how the extent and intensity of fishing effort has changed over time. Fishing effort is not homogenous, but varies both spatially and temporally due to many underlying factors. Each vessel weighs the various costs and benefits of fishing locations differently, but certain areas are more preferred than others. This leads to increased fishing intensity in predictable spatial locations. The underlying habitat and fish populations in these areas are more exposed to the degradation and loss of diversity caused by repeated fishing pressure (Parnell et al. 2010). Sessile organisms such as sponges and corals are removed by bottom-trawling, reducing diversity. Mortality of non-target species is proportional to the number of times trawled (National Research Council Staff 2002).

Both the implementation of MPA closed areas and the changing seasonal sea ice levels were used to study changes in fleet behavior over the course of the study period, 1993-2015. The findings point to the much broader implications of the intensity of bottom-trawl impact on the benthic layer ecosystem and shows how the bottom-trawl fishing fleet may respond to future MPAs and increased fishing ground availability due to global climate change. Understanding how bottom-trawling effort changes and evolves in response to these outside pressures is integral to the continued sustainability of Alaskan commercial fisheries.

Results from this project show that fishing effort near MPA boundaries have increased activity after the instatement of the closed area. This may have unintended consequences on the area, particularly if the fleet moves into a previously undisturbed or lightly trawled area due to the displacement. This would greatly increase the impact from bottom-trawling gear on the benthic habitat and removal of benthic species. The goal of protected areas is to protect valuable resources within the boundaries, but creation of the boundaries must take into account what will happen directly outside the protected area boundaries.

Climate change and its effects can be broad and complex, including changes in water temperature, water currents, and species composition. Winter 2015-2016 was the warmest winter for the Arctic in satellite record, and sea ice extent has declined 13.4% per decade in the Arctic region since satellite observations began, which includes the Eastern Bering Sea (Cullather et al. 2016). This would cause low ice effect years to increase in frequency and intensity. Results from this analysis were inconclusive on the effect of sea ice concentration levels. On average, the total annual catch and total number of hauls increased in normally ice affected areas on lower ice effect years, but no pattern in effort hot spots was detected. Different parameters of seasonal sea ice such as maximum extent or sea surface temperatures may have produced more conclusive results. Also, the fishery dataset includes only annual totals; totals from only the winter season may have been more beneficial in visualizing the effect of sea ice.

The study could also benefit from additional data attributes for Alaskan bottom-trawl fishing effort. Area swept by bottom-trawl gear and haul total duration could more accurately portray the impact caused by fishing activity in a particular area. Using data from individual vessels and individual hauls would provide the most detailed information. For this study, this amount of detail was not necessary, but could be very beneficial to future research.

Organization into the space time cube was integral to the completion of this project. The cube has proven through this analysis of the bottom-trawl fleet to be a valuable structural format in spatiotemporal trend analysis. Looking at neighbors in both space and time improves the assessment of clusters in the dataset. Each time slice is not considered by itself, but as part of the larger time period. This tool has been traditionally used for crime statistics. Showing the space-time cube has a wider application in very different fields has been achieved through this analysis.

Some improvements would benefit the application of the space-time cube to future projects. The most troubling portion of this project was re-gridding the dataset to fit the specifications of the tool. If the tool allowed for aggregation into a user-supplied grid, the analysis could be more appropriately tailored to individual projects. As the number of tools available to use with the space-time cube in ArcGIS Pro continues to grow, the potential for this tool will be even greater.

The space-time cube's utility could also be improved by providing ways to better share three-dimensional visualizations. A strong component of the space-time cube's function is the ability to interact with the cube, navigating through the layers, row by row or slice by slice. An area of interest would be better understood by manipulating the three-dimensional image as needed. End users cannot obtain the full experience in static images or fly-through videos.

5.6. Future Research

Future research using the space-time cube results could be beneficial to many aspects of fishery trends and retrospective spatial analyses. Pairing the results with benthic habitat information would give a more in depth understanding of the species and habitat types being affected by bottom-trawling. Smooth sheet bathymetry models of the Aleutian Islands and parts of the Gulf of Alaska were completed in 2017, with the Bering Sea and remaining areas of the Gulf of Alaska expected to be released (NOAA 2016). The smooth sheets include bathymetry, substrate types, and features that would allow for detailed habitat identification. Deep-sea corals are highly susceptible to bottom-trawl activity and conservation efforts would be greatly benefited by a more detailed analysis of the interaction of fishing effort and coral habitat areas.

The results of this analysis bring several more questions to the forefront that could be addressed through future research. The trend and hot spot results show that fishing effort spatial patterns vary significantly from year to year and change over time. Additional research could began to answer what causes these changes. MPA closures and sea ice concentration were shown as just two of many influencing factors that determine when and where fishing effort occurs in the Bering Sea, Aleutian Islands, and Gulf of Alaska.

Going beyond the bottom-trawl fleet, the organization of the space-time cube could be applied to other fisheries or regions with great benefits. The occurrence of bycatch events could also be analyzed using the space-time cube. The data have the potential to better represent fleet behavior in prediction models, cost/benefit analyses, socioeconomic impact analyses, and many other topics of interest for fisheries sciences. Fisheries science will benefit from a much stronger spatiotemporal element in future research.

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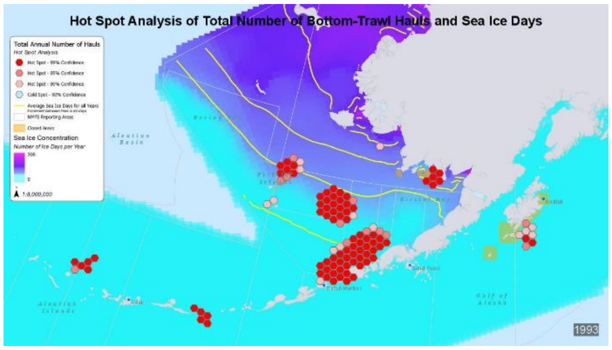
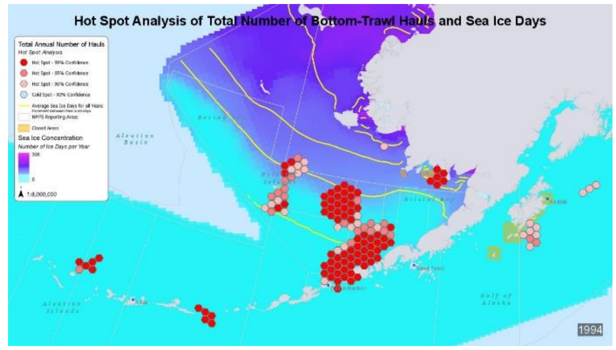
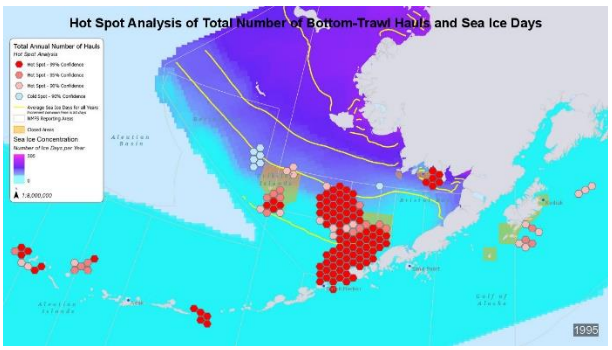
Appendix A Animation Slides for Total Number of Hauls



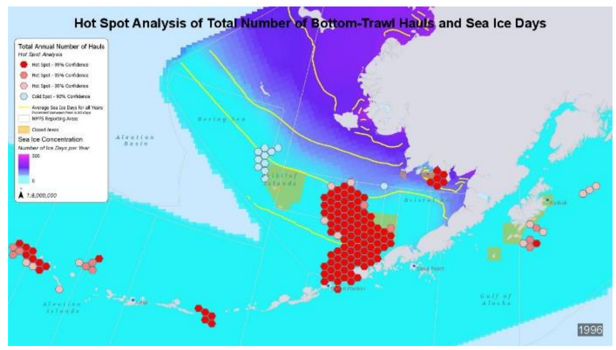
31. 1993 Low Effect



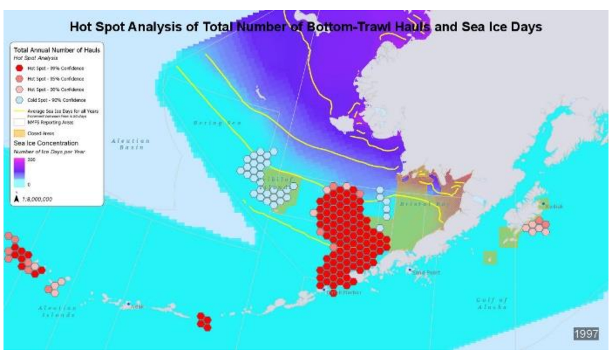
32. 1994 High Effect



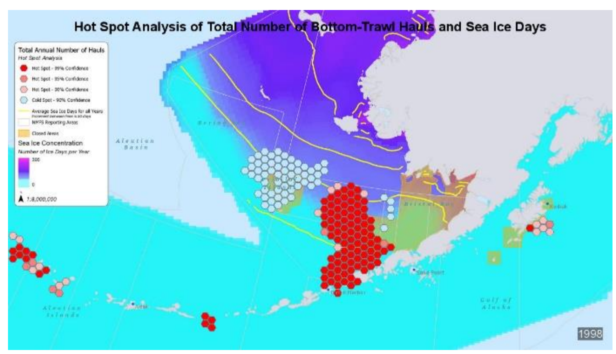
33. 1995 High Effect



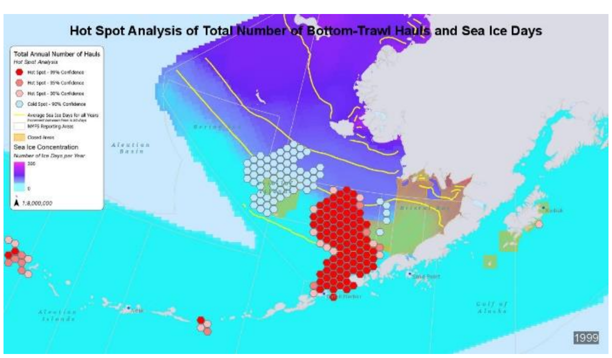
34. 1996 Average Effect



35. 1997 Average Effect



36. 1998 Average Effect



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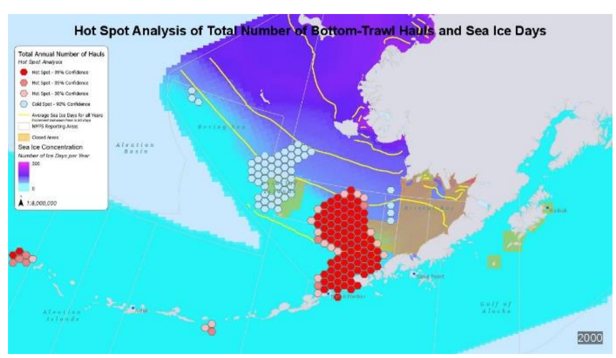

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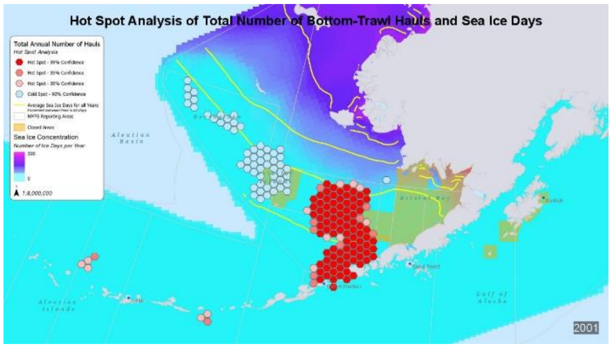
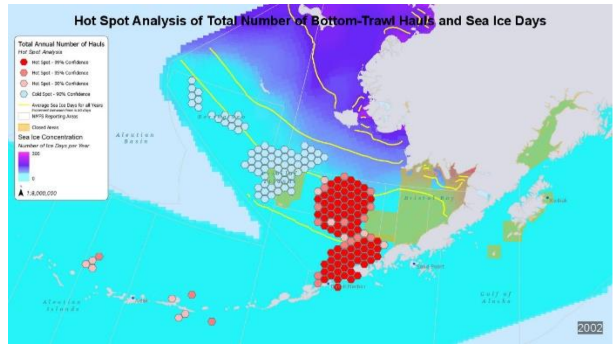
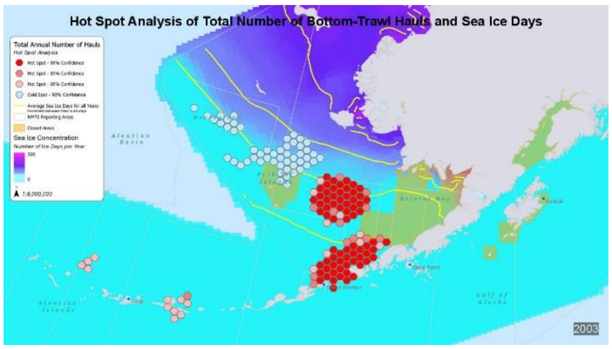


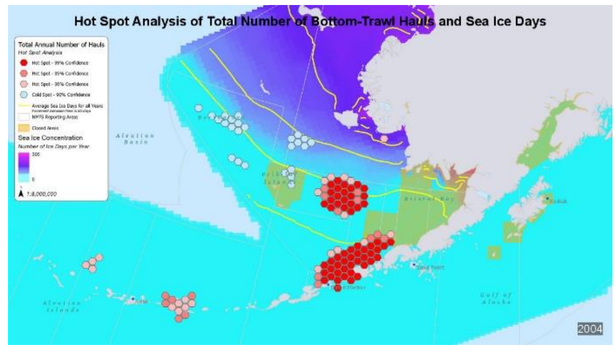
39. 2001 Low Effect



140. 2002 Low Effect



41. 2003 Low Effect



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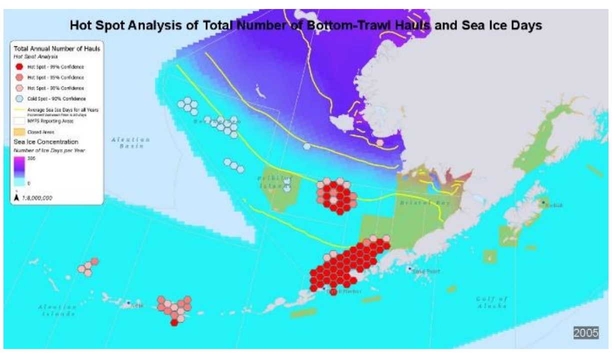

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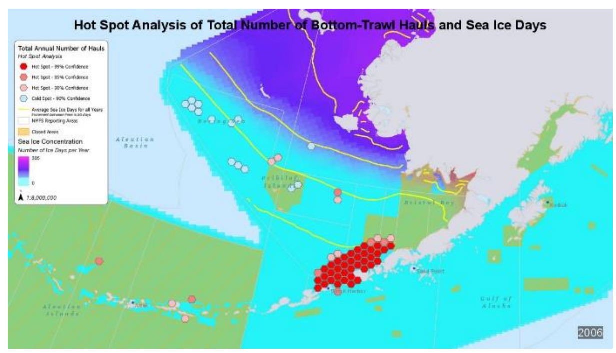

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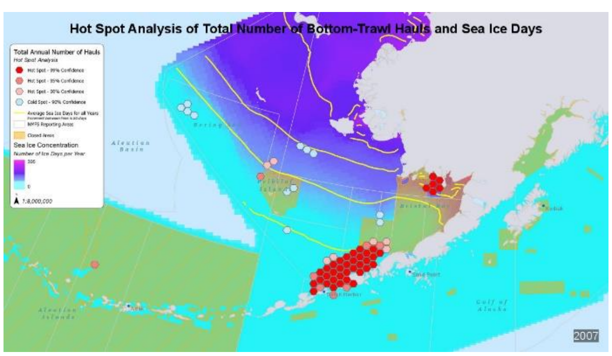
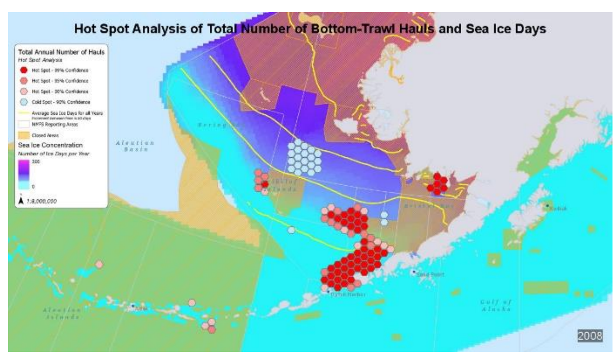
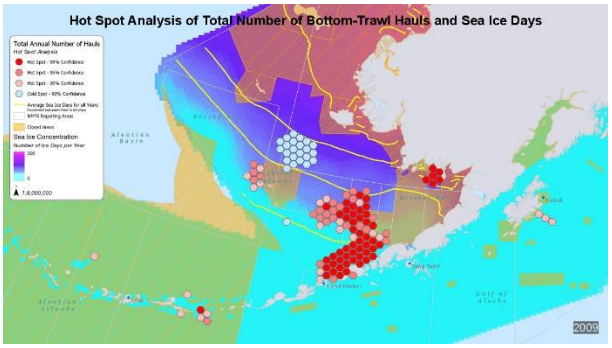


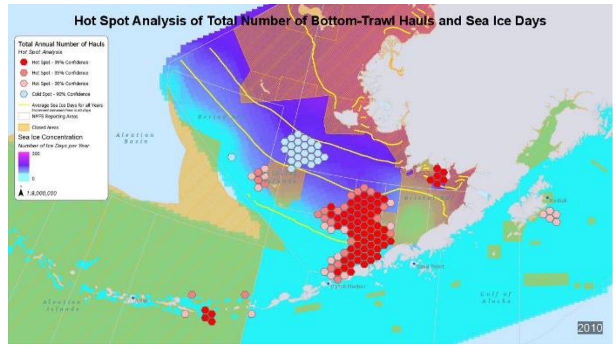
45. 2007 Average Effect



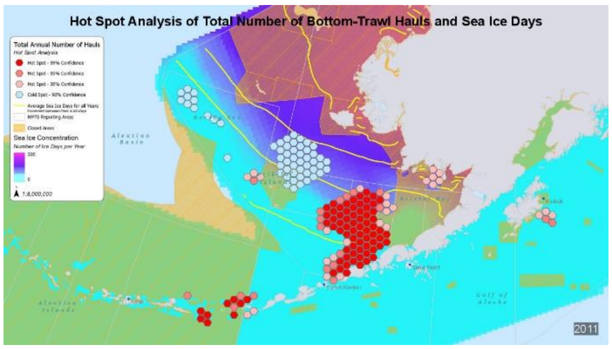
46. 2008 High Effect



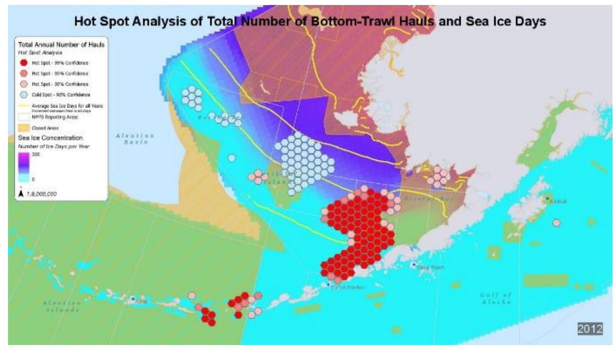
47. 2009 High Effect



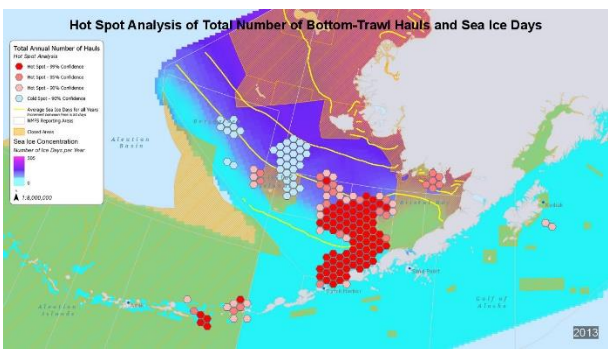
48. 2010 High Effect



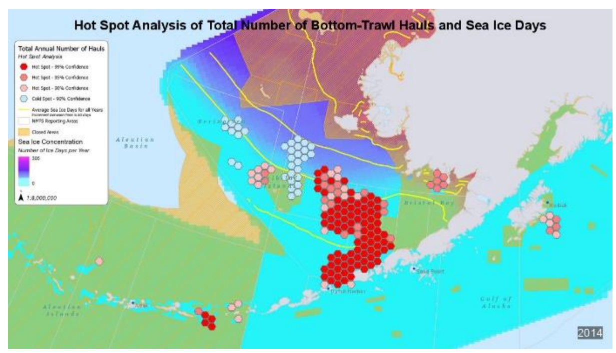
49. 2011 Average Effect



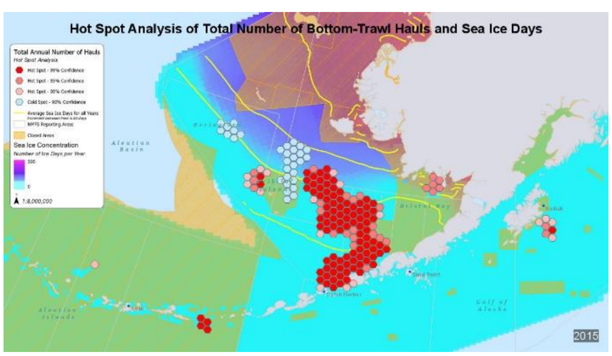
50. 2012 High Effect



51. 2013 High Effect

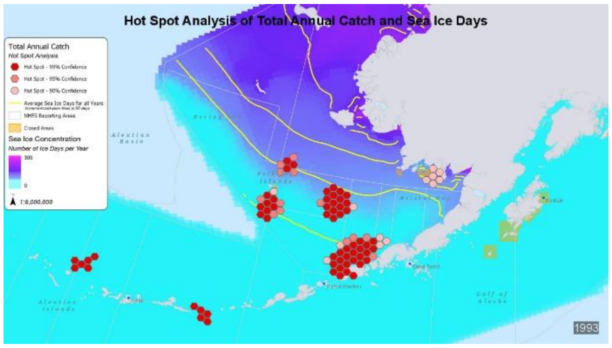


52. 2014 Low Effect

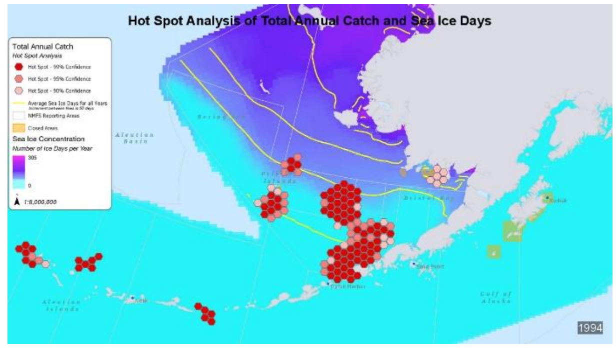


53. 2015 Low Effect

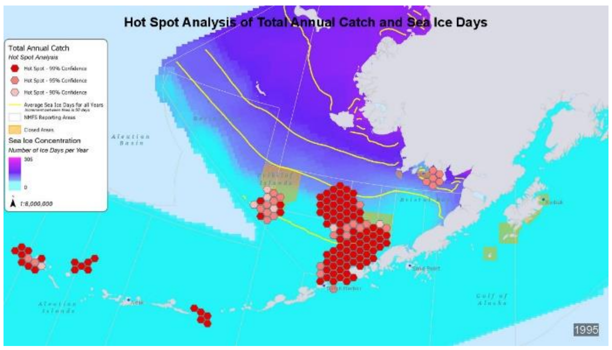
Appendix B Animation Slides for Total Annual Catch



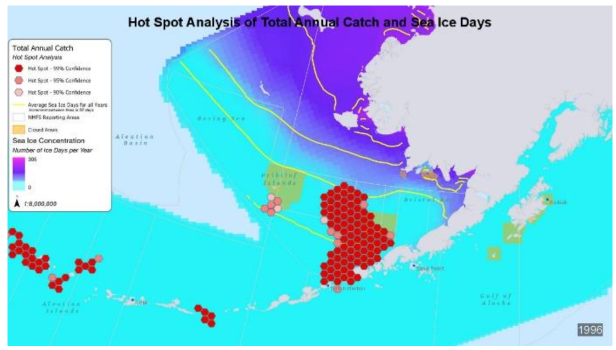
1. 1993 Low Effect



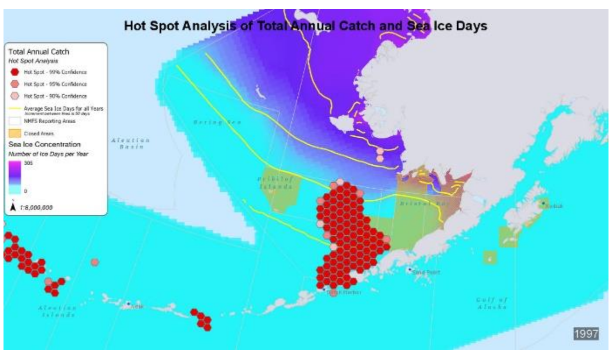
2. 1994 High Effect



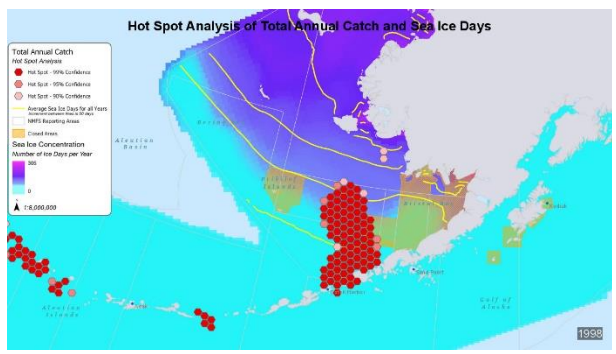
3. 1995 High Effect



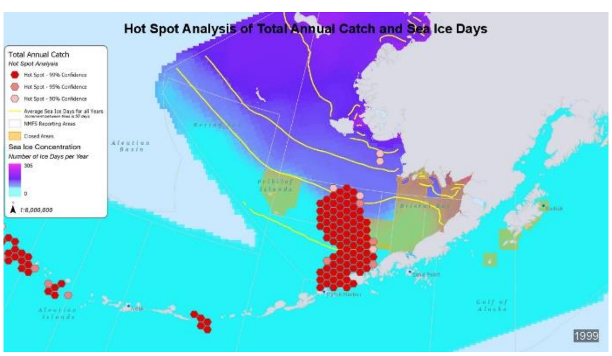
4. 1996 Low Effect



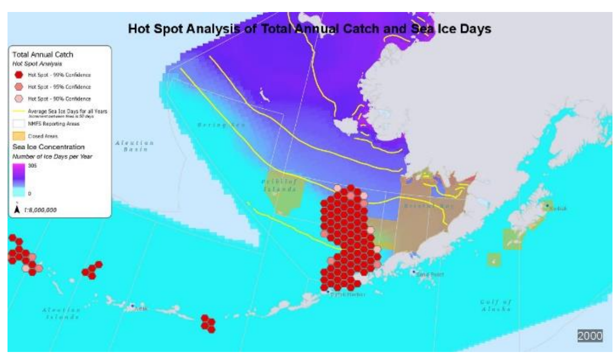
5. 1997 Average Effect



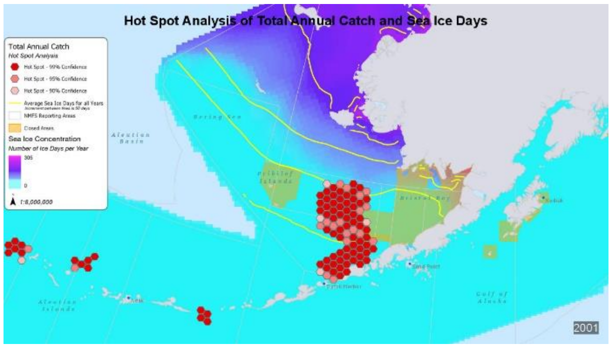
6. 1998 Average Effect



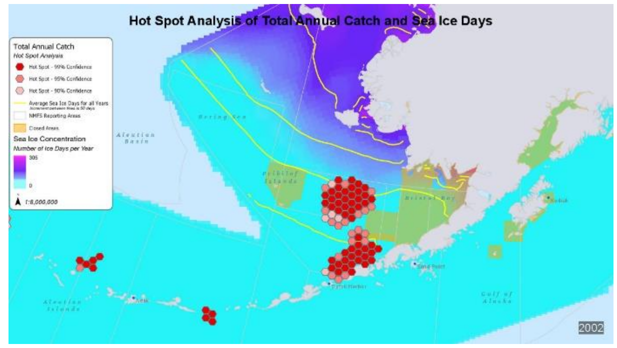
7. 1999 High Effect



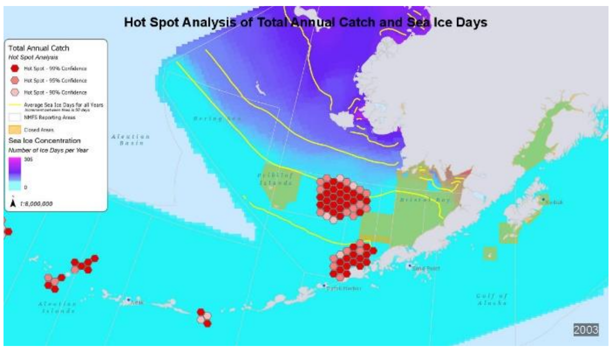
8. 2000 Average Effect



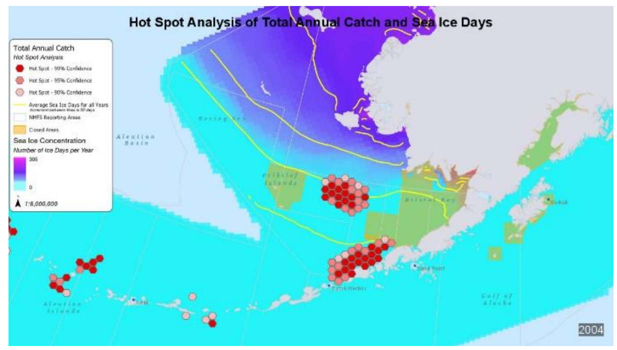
9. 2001 Low Effect



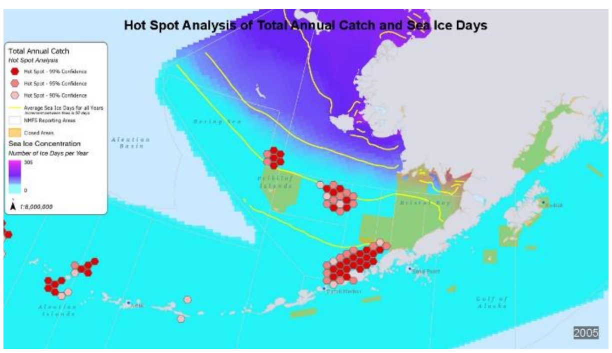
10. 2002 Low Effect



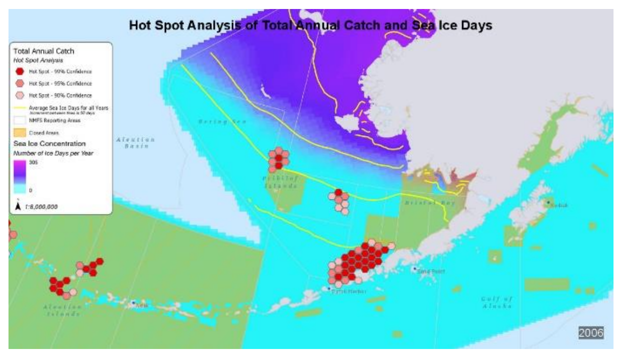
4. 2003 Low Effect



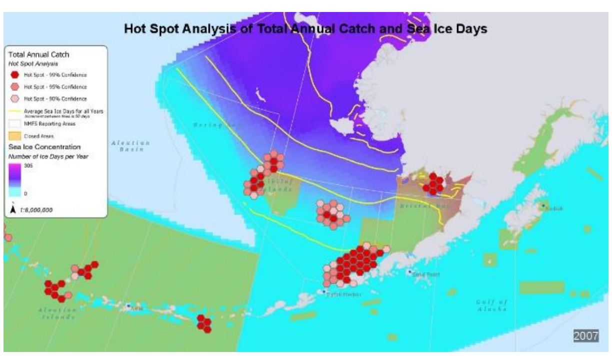
12. 2004 Low Effect



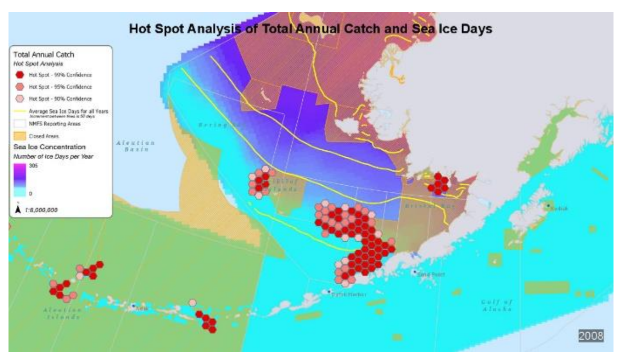
13. 2005 Low Effect



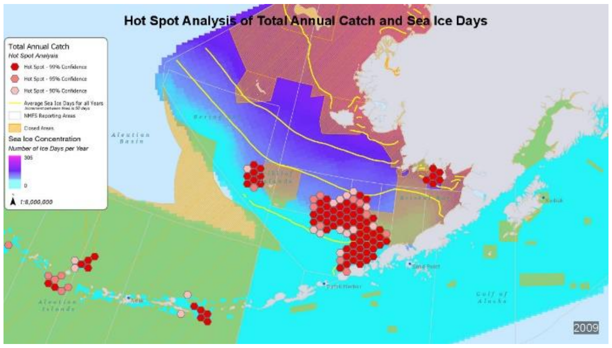
14. 2006 Average Effect



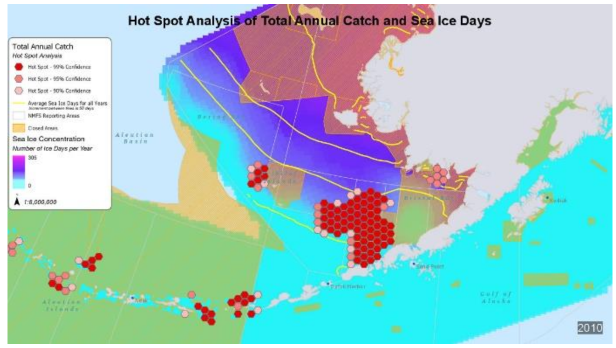
15. 2007 Average Effect



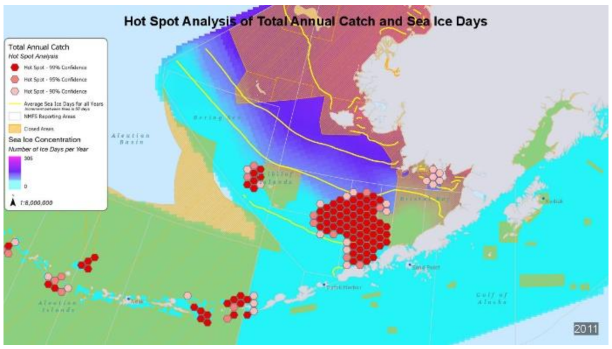
16. 2008 High Effect



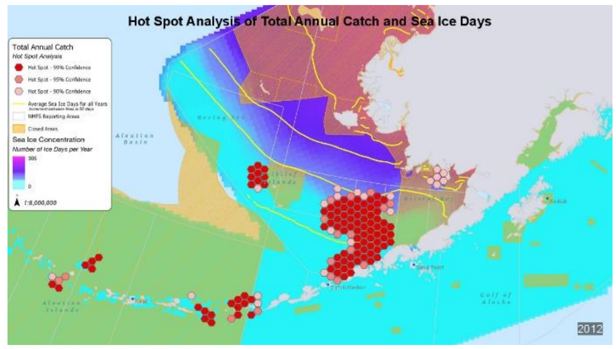
17. 2009 High Effect



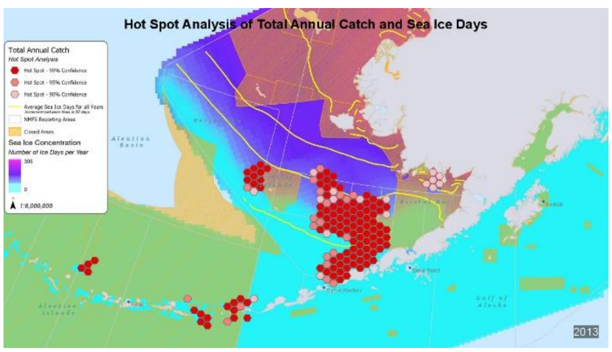
18. 2010 High Effect



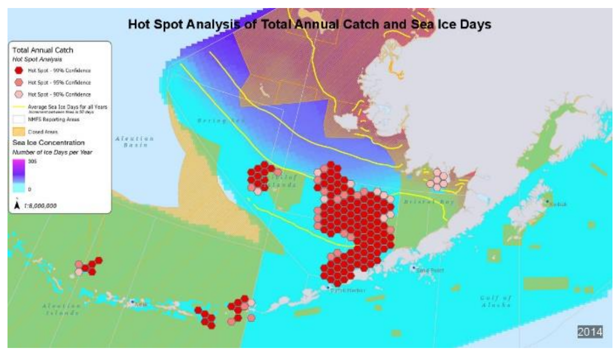
19. 2011 Average Effect



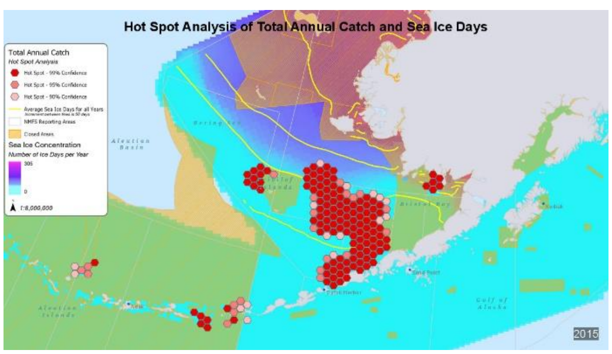
20. 2012 High Effect



21. 2013 High Effect



22. 2014 Low Effect



23. 2015 Low Effect