Geospatial Preference Modeling and Real-Time Catch Reporting in Support of an Atlantic Bluefin Tuna Avoidance System

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Abstract

The goal of this project is to use the Geospatial Preference Modeling to predict Atlantic Bluefin Tuna behavior. This will form a foundation for the development of the Atlantic Bluefin Tuna Avoidance System for the North Atlantic Pelagic Long Line (PLL) fleet. We have collected non-aggregated real-time catch data from PLL vessels and examined environmental preferences of the Atlantic Bluefin Tuna. The data is used to develop an integrated depiction of the Atlantic Bluefin Tuna "hotspots" based on movement patterns, biological state, and oceanographic conditions.

Introduction

Atlantic Bluefin Tuna (ABFT) is regarded by many as one of the most highly-stressed populations in the ocean. Stringent management measures have been put in place at the international level to ensure the survival of this species, but incidental by-catch of ABFT in non-ABFT targeting fisheries still occurs. In the US, this most frequently occurs in the Pelagic Long Line (PLL) Fisheries of the North Atlantic and Gulf of Mexico, which targets Swordfish.

Fisheries managers face difficult decisions on how to reduce bycatch of ABFT while minimizing, to the extent practical, adverse social and economic impacts of management measures. Driving this difficulty is a relatively limited understanding of the ABFT behavior, which is largely due to the assumptions made from the current data available which is aggregated. More precise data is needed to better understand the ABFT behavior and movements.

GeoEye, Inc. and the University of Massachusetts Large Pelagics Research Center have constructed a Geospatial Preference Model (GSP) that predicts the movements of ABFT. The model incorporates historical by-catch, as well as behavioral and environmental data across the Area of Interest (AOI) under consideration – the Florida East Coast (FEC) region. An environmental model was built with oceanographic and other "factor" data sets. The model is trained with "event" data, which is the fish bycatch provided by the PLL vessels. The model analyzes this information to develop a pattern or "geospatial signature" (hot spots) of the ABFT preference and movements. This information can be used by the fishing industry to reduce the bycatch of the ABFT.

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The views expressed herein are the author's and do not necessarily reflect the views of NOAA or any of its sub-agencies.

Objectives

These are the following objectives that have been set for the Atlantic Bluefin tuna avoidance system:

1. Build an effective geospatial preference model for predicting the location of ABFT habitats.
2. Employ enhanced reporting measures to collect real-time pelagic longline (PLL) catch data and incorporate it into the model for daily production of hot spot maps.
3. Automate the modeling process to produce timely, predictive hot spot maps of ABFT movements.

Methods

General Overview

Atlantic bluefin tuna (ABFT) (Thunnus thynnus) disperse widely throughout the North Atlantic. Unlike many other highly migratory species, they have a broader horizontal and vertical range (Mather et al., 1995; Galuardi et al., 2010) thermal tolerance (e.g., Carey et al., 1971), and greater plasticity in their life history, spawning areas, and inter-annual migration patterns than currently recognized (Fromentin and Powers, 2010; Chapman et al., 2011). A number of assumptions exist for the presumed western stock about stock mixing (Lutcavage et al., 1999; Block et al., 2005), geographic extent (Sibert et al., 2006), age of maturity (Goldstein et al., 2007) and likelihood of additional spawning grounds (Mather et al., 1995; Lutcavage et al., 1999;Galuardi et al., 2010). Some of these assumptions may require revision to be consistent with observations.

There is a growing body of fishery independent information on ABFT movements, trophic relationships and habitat utilization from electronic tag studies and biological sampling. This information should help improve management options, and help pelagic longline (PLL) fleets reduce non-target catch. Currently, however, such information is not utilized in this capacity. The Geo-Eye team will offer a total analysis of both fisheries dependent and independent data currently available. We will also employ enhanced reporting methods and state-of-the-art tagging technology to collect new data of each variety to be used in the development of a GSP model capable of predicting ABFT movements and behavior.
The area of interest for this experiment will be the Florida East Coast (FEC) PLL fishery.

Dispersal patterns portrayed by PSAT datasets (e.g. Galuardi et. al, 2010) document when and where ABFT could potentially overlap with the FEC or other PLL fleets as they travel to and from feeding and spawning areas. Habitat utilization and oceanographic analysis from PSAT tags offer different information than catches or logbook data. Dispersal and depth patterns generally portray three dimensions of where bluefin tuna are – not just when and where they bite. Having an understanding of whether tunas are feeding, spawning or migrating through fishing areas in addition to catch data is useful for understanding patterns in availability or vulnerability to capture (Brill and Lutcavage, 2001).

LPRC scientists have examined annual dispersal patterns of ABFT from foraging grounds in New England and Canada to presumed spawning grounds and back (e.g., Wilson et. al., 2005; Sibert et. al., 2006; Galuardi et. al., 2010; Galuardi and Lutcavage, 2012). For example, Bluefin tuna has been tracked from Canadian feeding grounds by quarter in 2005-06 (Galuardi et al., 2010). In all but summer, adult bluefin tracks overlap with areas currently fished by the Florida PLL fleet. A few tracks of juvenile ABFT also indicate habitat utilization in the region (Galuardi and Lutcavage, 2012). In April- May, 2012, LPRC obtained ABFT gonads, otoliths and genetic samples in order to characterize the biological status of fish in that region (roughly, 28 °N 78 °W). Catch data from the Marine Stewardship Council (MSC) certification of the Dayboat Seafood Company (DBS) also documents ABFT bycatch results in winter months (MRAG Americas, 2011), consistent with tagging results. These observations indicate that the FEC will provide a suitable area of study for the purposes of this research.

The GeoEye team conducted research with the LPRC and vessels in the DBS fleet (primary FEC PLL fleet) to examine real-time catch patterns and GSP of ABFT over nine months in the FEC region. Data collected used to build the GSP.

Non-aggregated real-time catch data from PLL vessels:

Accuracy and privacy concerns have driven traditional fishery catch data to be analyzed and reported in an aggregated fashion. Day Boat Seafood (DBS) LLC's cooperation helps eliminate the accuracy issue for this project. Combining real-time monitoring of PLL catches for all species with PSAT and associated environmental factor data will provide the ideal resolution of ISS data to validate the GSP model.

GeoEye's Osprey handheld reporting device will help improve the quality of the data. Osprey transmits a real-time message with a GPS position, date, time, species caught, and size category back to a GeoEye hosted catch database using Inmarsat's Isat-M2M network. GeoEye currently provides the tracking and reporting service described here to fisheries in The Republic of the Maldives, Trinidad and Tobago, Ghana and the Republic of the Seychelles. The Osprey is currently under consideration by a number of other government and multinational fisheries management organizations.

Catch data validation was provided through 100% observer coverage on each data collection trip. Since DBS is an MSC Certified organization, their rate of observer coverage is higher than average for the North Atlantic PLL fleet. This means NMFS will already have observers on the DBS vessels regularly throughout the year. While DBS is aware that the vessel selection process in the NOAA Observer Program is intended to be random, the company welcomes a higher percentage of regular observer coverage during the research period.

ABFT behavioral data:

Fish Tag Project for Fishery Independent Data Collection and Analysis

Twelve electronic tags (Wildlife Computers) will also be deployed during the longline trips during April to June, which is the known spawning period of bluefin tuna in the Gulf of Mexico. Data will be analyzed and corrected for error by the LRPC team.

This combination of fisheries dependent and independent data will provide an unprecedented opportunity to observe bluefin tuna movement and longline gear interaction simultaneously and to highlight preference factors for ABFT ISS that may previously have been unknown to the fisheries and management communities. This represents a significant advancement beyond current usage of electronic tag data to inform range prediction management systems (e.g., Hobday et al., 2011).

Near-Real-Time Environmental Data Production and Delivery

Environmental data taken into consideration include, but are not limited to, satellite data such as sea surface temperature, chlorophyll concentration, sea surface height anomaly, ocean currents, subsurface temperature layers, thermocline depth, and salinity. For more than 16 years, GeoEye has been providing a near-real-time operational oceanography service that offers this suite of variables, in addition to weather information. All data sets must be properly formatted and individually registered for ingestion into the modeling process.

Geospatial Signature

The primary tool used in development of the ABFT GSP is an application called Signature Analyst (SA). SA is a spatial decision support system that attempts to describe the relationship between Intelligent Site Selection (ISS) event locations and a set of environmental factors using Geospatial Preference (GSP) models. By attempting to model in the decision space of the actors, the GSP models can provide significant improvement over standard spatial modeling techniques.

SA incorporates a modeling methodology for events occurring within a geographic space. Actors with complex decision-making capabilities initiate these events. While the actors make spatial decisions (site selection), they use more than just spatial coordinates. They decide based upon a complex combination of the attributes and features of one location compared those of all other available locations. Spatial coordinates providing an index to map a particular site to its corresponding feature set. GSP modeling refers to the methodological framework specifically designed to understand the decision making process of the actors as well as predict where future events may occur.
GSP models treat the events as coming from an ISS process, a special class of point process arising from spatial decision-making. The methodology attempts to incorporate the actors' preferences by including the

features that are thought to influence (or are associated with the features that influence) the ISS process. In this case, those features will include near-real-time environmental data, such as AVHRR, MODIS, and other remotely-sensed information.

Feature Space Preference Models

Methods dealing with general point processes have been developed around environmental phenomena, which assume a smooth spatial dependence model and the lack of discontinuities (Dueker and Kjerne, 1989). These methods perform well for modeling spatial phenomena that have smooth spatial autocorrelation such as sea surface temperature, forest composition, water table depth, and pollution spreading. However, when these techniques have been applied to the social sciences (and ISS processes in particular), the results are not as promising (Lavigne-1999).

Feature space preference (FSP) models (Brown, Dalton, and Hoyle-2004) address this problem by directly considering the decision making process of the actors. The purpose of this modeling effort was to gain insight into the actors' selection preferences by observing sites that were selected previously. By looking at the decision space as a set of environmental variables rather than a set of geographic coordinates, a closer fit to the true selection criteria was derived and more accurate models were created.

Model Training using Event Data

In the context of this application, event data includes both fish catch and tagging data. Data sources include the Marine Stewardship Council's (MSC) certification study for the Day Boat Seafodd Company and the LPRC's archive of tag data. The LPRC team will provide validation for historical fisheries data they have obtained.

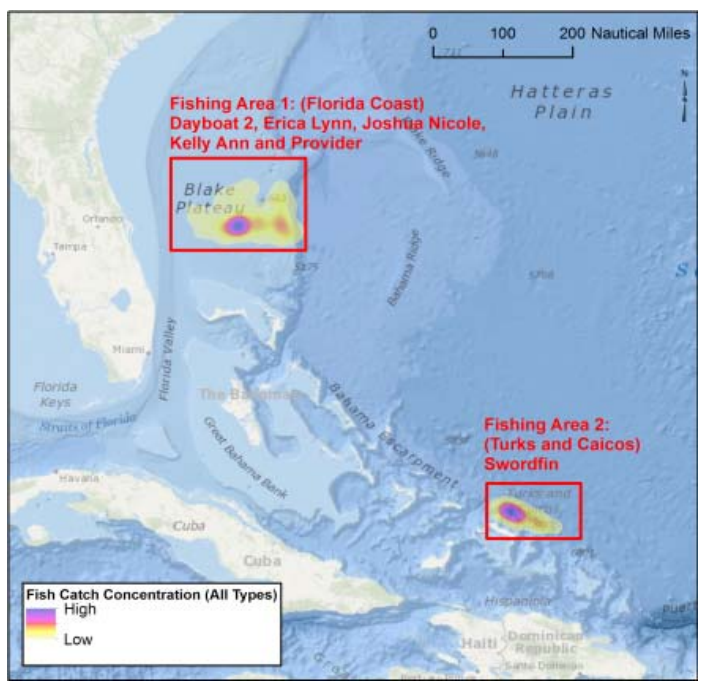
Projects within SA will be setup to manage the temporal aspects of the environment and the event data to account for signature changes that occur due to seasonal migration of ABFT. This means the model will have to run over a long period of historical data to observe performance and generate initial conclusions. Different combinations of data may yield alternative results at different times of year. The FSP process eliminates human bias towards the relevance of a certain factor data set over another. Thus, hotspots models for different seasons can be derived. A number of performance metrics are provided by SA throughout the modeling process. This feedback will help shape conclusions, project reporting and next steps.

Results

Over-All Catch Summary

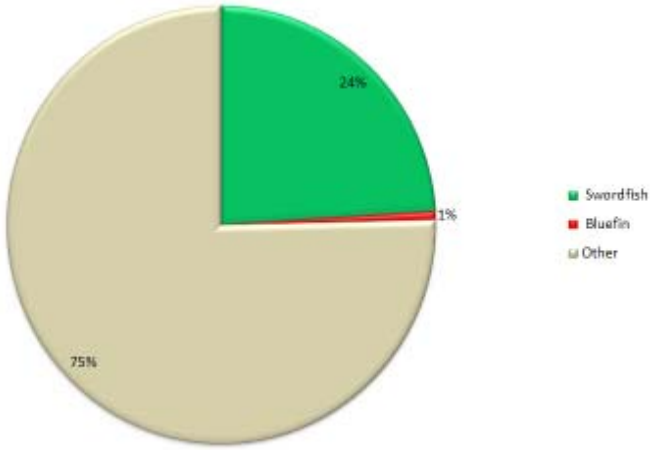
Geoeye analysts performed preliminary analysis of catch data reported between 12/31/2013 – 3/30/2014. The following 7 boats had historical fishing data that was included in the analysis: Dayboat2, Erica Lyn, Joshua Nicole, Kelly Ann, Provider, Swordfin and Vitamin C.

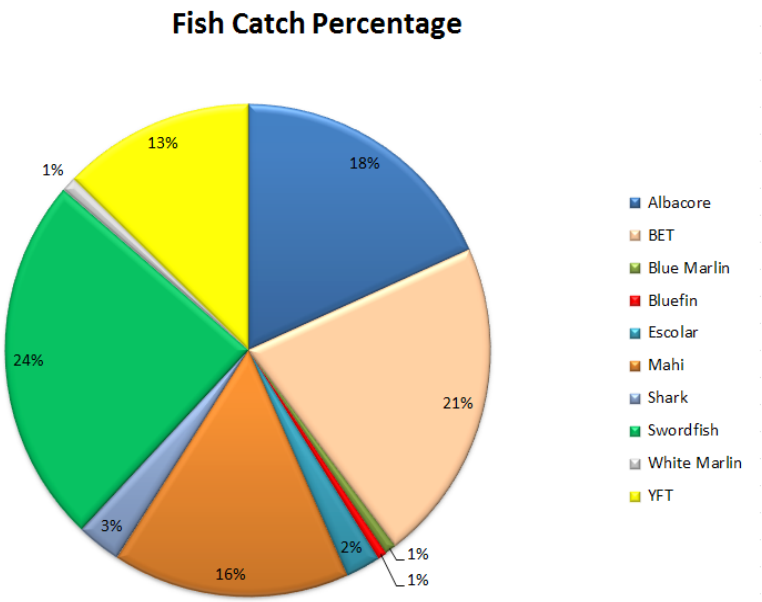
Fishing was conducted primarily off the Florida coast, with data from a single boat (Swordfin) recording fishing and catch data off the Turks and Caicos Islands. The graphic below depicts the areas of catch concentrations:

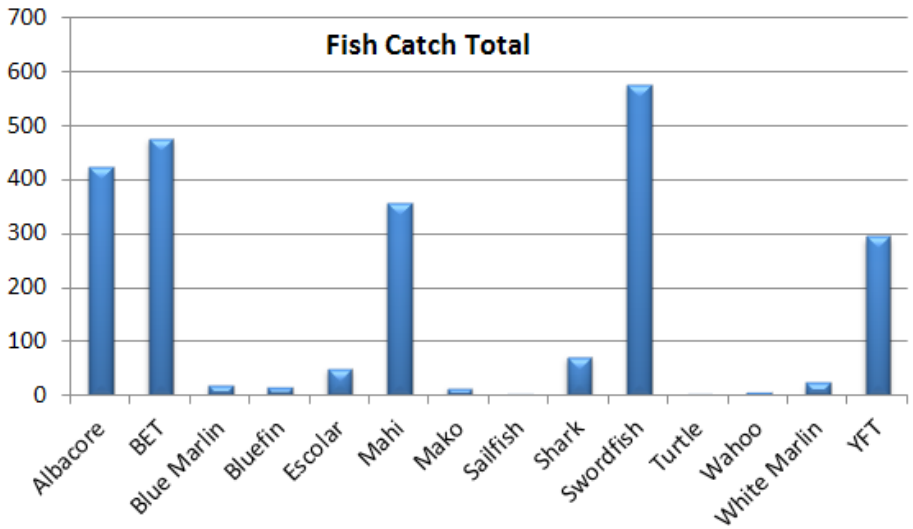


A total of 2,460 fish were caught in the three month period. Of the fish caught, 24% (591) were Swordfish, and less than 1% (15) was bluefin tuna. Approximately 75% of all catches were not swordfish or bluefin tuna.

The graphics below depicts the percentage and total number of fish caught:





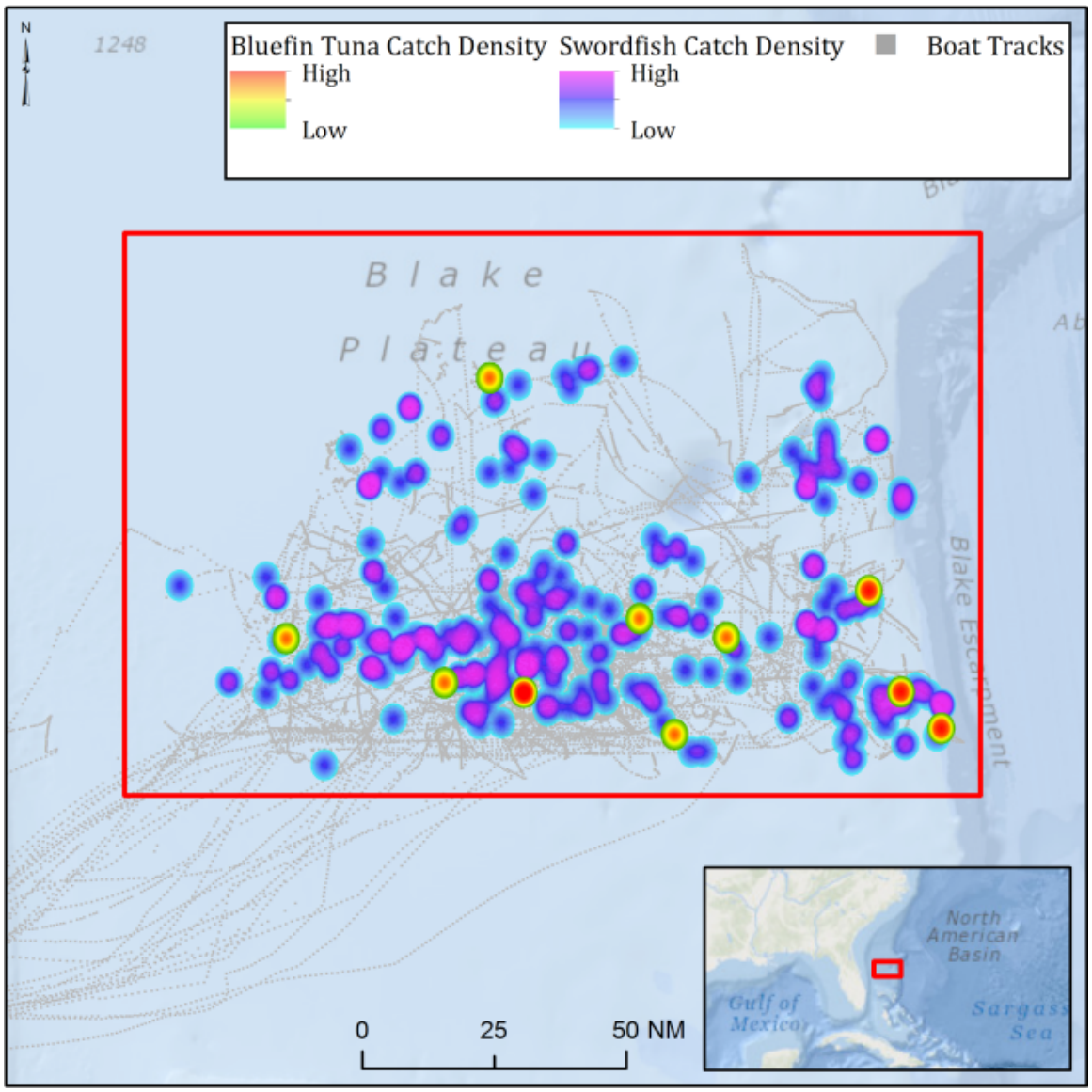


Conclusions

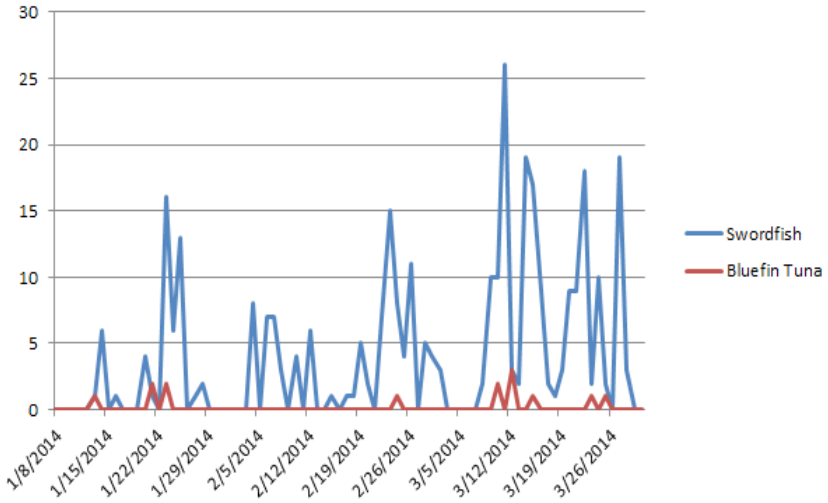
The focus area of analysis was the area identified as "Fishing Area 1", off of the coast of Florida. Within this 14,748 nm2 area, there were 329 swordfish and 14 bluefin tuna catches. The catches represent "Event" data that can be measured against the environmental conditions on the same day to better distinguish optimal fishing conditions.

Te frequency of catches dictate the number of days the analyst must normalize environmental conditions to most accurately reflect conditions at the time of catch. Thus far in the study period and within "Fishing Area 1," the catch frequency of species of interest is as follows:

Average	Swordfish	Bluefin Tuna
Days between being caught	0.2	5.5
Catch per day over 3 months	3.7	.16
Number per catch	6.7	1.6



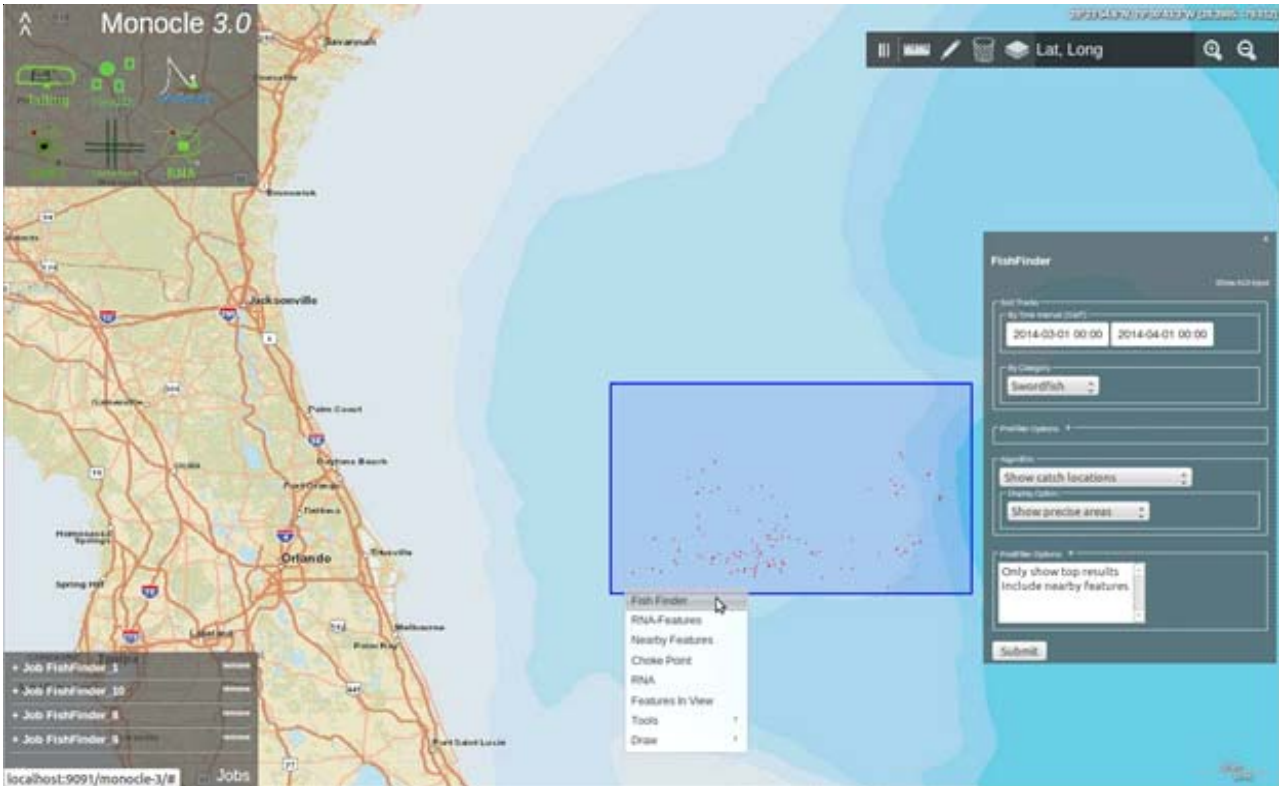
Nearly seven swordfih are caught each day while less than two bluefin tuna are caught every five and a half days. This rate of frequency suggests that environmental data for modeling bluefin tuna may have to be normalized over a longer period of time than swordfish to have enough "event" data to measure against the model. Future data collection and analysis will ultimately dictate a conclusive decision to the environmental data normalization process.

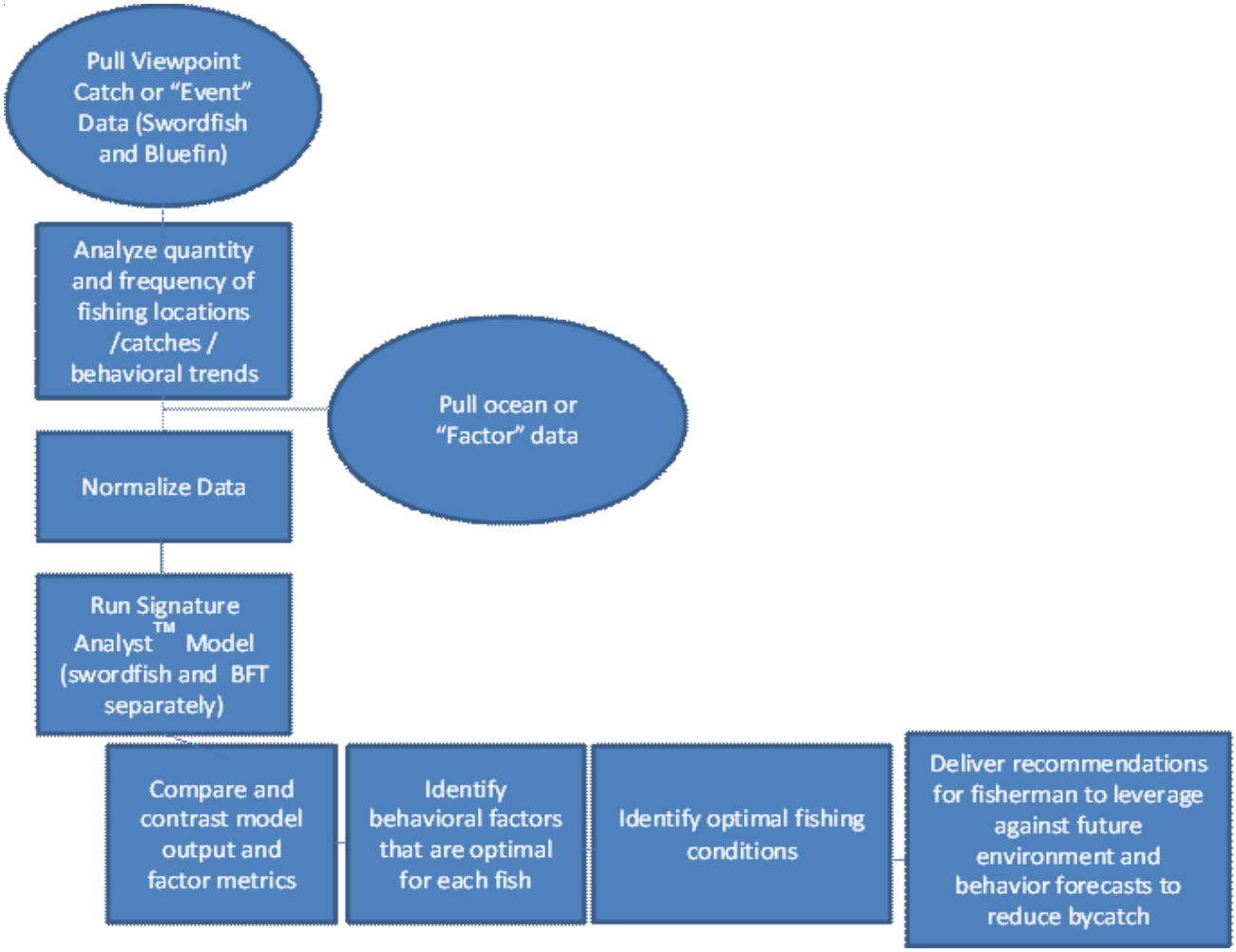


Delivery Mechanism

Monocle-3 is an extensible web map interface supporting applications that can communicate with the map, the vector products they create, and amongst other widgets.

Fish Finder, part of the Monocle-3 development, is a widget for performing analysis on bycatch reduction data collected by the Digital Globe Marine Services Osprey trackers. The widget ingests Osprey data with location, date, catch type, and related information. Currently it supports user interaction to select time ranges, areas of interest, fish type, and operations to be performed on the data. Ultimately, the end state of the Fish Finder widget will include capabilities that allow for reduction of bycatch of Bluefin tuna.





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