# Spatiotemporal Distributions of Species Detected within Virginia's Offshore Lease Areas

Volume 1: Sandbridge Shoal Marine Minerals Lease Area

**U.S. Department of the Interior
Bureau of Ocean Energy Management
Sterling, VA**

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Spatiotemporal Distributions of Species Detected within Virginia's Offshore Lease Areas

Volume 1: The Sandbridge Shoal Marine Minerals Lease Area

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DISCLAIMER

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ABOUT THE COVER

Monitoring a Vemco® VR2AR receiver, Christian Hager, Chesapeake Scientific LLC.

ACKNOWLEDGMENTS

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List of Abbreviations and Acronyms

Short Form	Long Form
ACT	Atlantic Coast Tag data base
AR	VR2AR
BOEM	Bureau of Ocean Energy Management
CRA	Cable Region Array
CS	Chesapeake Scientific LLC
DPS	Distinct Population Segment
ESA	Endangered Species Act
IRI	Indices of Relative Importance
Khz	kilohertz
NMFS	National Marine Fisheries Service
SBA	Sandbridge Array
SIRI	Site Specific Index of Relative Importance
USN	United States Navy
VA WEA	Virginia Wind Energy Area
WFA	Wind Farm Array

1   Introduction

Chesapeake Scientific LLC (CS), in collaboration with the United States Navy (USN) and HDR Inc., conducted two distinctly different marine acoustic monitoring research projects off the coast of Virginia for the Bureau of Ocean Energy Management (BOEM). The results of each are presented in a separate volume. This is volume 1. Both projects relied on data collected through the use of a passive array of Vemco® receivers. In both cases, detection data was collected on any and all species carrying Vemco® (69 Khz) transmitters. The data presented in this volume is associated with the array deployed off of Sandbridge, Virginia in the marine mineral lease area, also known as a borrow area, that is a critical sand resource for coastal resiliency projects. This array is referred to as the Sandbridge Array (SBA). The data found in Volume 2 of this study was collected in preparation for the potential development of an offshore wind lease referred to as the Virginia Wind Energy Area (VA WEA). The objective of both research efforts was to provide whatever detection data could be attained through a simple monitoring exercise in order to improve our understanding of the spatiotemporal distributions of tagged species. The goal of this project was to obtain data that will enable resource managers to better understand impacts to marine animals and habitats and formulate relevant mitigation measures especially for those listed on the Endangered Species Act (ESA). This detection data is the only spatiotemporal acoustic data available on species carrying transmitters in these two lease regions and thus, by default, it is the best available data.

Acoustic telemetry is a valuable management tool. Typically, individuals are telemetered to make inferences about a particular species. As project objectives dictate, individuals receiving transmitters may be specific to a location, sex, life stage, natal population, etc. and as more individuals are telemetered, the inferences a researcher can make become more powerful and far-reaching. Conversely, as was done in this project, a region can be monitored for detections of telemetered individuals to better understand presence/absence in that area. These passive monitoring studies are limited to presence/absence reports because of the underlying biases unintentionally introduced by the researchers actively implanting transmitters into specific individuals for their own research purposes. Therefore, though this presence/absence data represents the best available science and achieved its assigned goal of providing data to guide decision making in order to minimize impacts inherent to activities within each BOEM lease; our interpretation of this data was severely limited because we lacked the meta-data on the biological attributes that influence movement and behavior (Clark 1968, Niklitschek 2001, Niklitschek and Secor 2005). Collecting this data would allow a much more detailed and appropriate examination of the factors that motivate movement and site occupancy. However, this data belongs to individual researchers with publishing rights that must be respected. In no way was the inclusion of this individual biological metadata within the scope of the research that resulted in the data for this report or the separate contract that paid for this report's construction. Also, no data was provided on the anthropogenic activities that took place congruently within the regions during monitoring. Consequently, how detection data during such activities was affected and/or if species illustrated any behavior response to such activities is impossible to determine.

Occupancy modeling (MacKenzie et al. 2017) has greatly expanded in use through the twenty-first century. However, to understand detection probability and occupancy frequency, we must have a basic understanding of the number of transmitters attached to certain species, which is not available here. To understand the probability of a species being in the area, we need to understand approximately how many individuals of that species existed and the proportion of the population that is carrying a transmitter. Population abundance for species with many transmitters is unavailable at this time. If a basic understanding of the population and the proportion carrying a transmitter were available, calculating a likelihood of presence is possible (Thompson 2004) but beyond the scope of this research project.

Without this information, the presence of a transmitter is still meaningful as it represents a transmitter that moved within the detection range of a receiver. A lack of a detection implies that no transmitters moved within detection range of a transmitter. Another complication is that detection distance is based on the size, transmission strength, and age of the transmitters, as well as abiotic and biotic variables at the time of data collection (Heapel et al. 2006, Simpfendorfer et al. 2008, Singh et al. 2009, Mathies et al. 2014). Therefore, detection distance is an ever-changing variable. This implies that a lack of detections on a receiver or at a particular location provides limited ability to make any reliable area-based inferences.

However, if a sufficient number of transmitters are in the system, which is available here in some cases, we may be able to infer given a large enough data set over time meaning from such simple presence absence detections to generally understand the timing of presence. When enough data is available across an array of receivers, detection data can even provide general guidance as to movements, occupation patterns, and even behavior. Given large enough sample sizes from each species distinct population segments (DPS) or contingents and seasonal migration and habitats occupation patterns for these biologically significant groups can be identified.

To maximize the usefulness of the detection data with regard to ESA-listed species, a site-specific index of relative importance (SIRI) model was applied. This determined the relative importance of the region over time (month) and space (receiver site) within the array. The advantage of the SIRI approach is that it does not rely on the type of information we previously identified as unavailable for this study, such as number of transmitters in the environment or the size of populations. Raw detection and researcher data is presented in the appendices as the primary objective of this paper is to disseminate information to improve our ability to inform resource management decisions. Any future improved investigations will require not only this data, but the metadata related to tagged fish and data related to congruent anthropogenic alterations to the region's environment that occurred during our monitoring to which we did not have access.

2 Methods

2.1 Data Collection Methods

No fish tagging was done for this project; rather, it was only passive tracking. Six VR2AR units produced by Vemco® were deployed in a gridded pattern within the SBA. These units are referred to as AR units because they automatically release; each is fitted with a lug that unscrews from the receiver when directed to do so via a computer operated hydrophone. A gridded pattern which roughly covered the edges of the lease and placed an additional receiver in the middle of the lease area in hopes that this multiple receiver approach could determine direction of travel (**Figure 1**). This pattern can also be used to test if spatiotemporal distributions are correlated with environmental attributes inherent to each site (Ingram et al. 2019, Rothermel et al. 2020), however, this was not our intent as the only attribute we collected was bottom water temperature and our sample site was so small that this variable was homogenous across all sites.
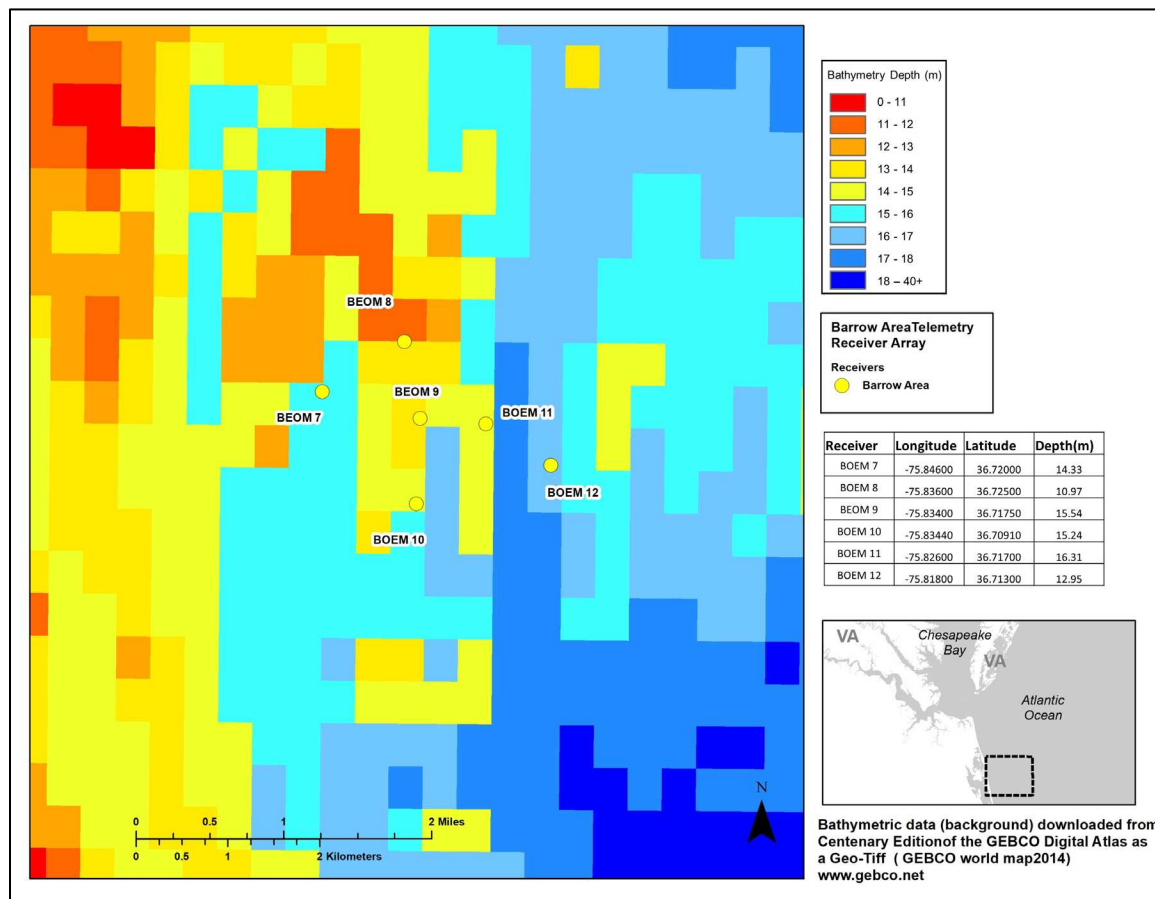
Figure 1. This lidar map gives the depth and locations of the six receivers deployed in the lease area.

Each AR unit was anchored to a 36.3 kg (80 lbs.) concrete block approximately 76.2 cm (2.5 ft) square and 10.2 cm (4 in) high. A piece of stainless steel cable was molded into each anchor and a rope woven in a circle connected the anchor to the AR's release lug and the AR to a buoy. This buoy kept the unit vertical in the water column approximately 1 m from the bottom. The anchor and remote release mechanism (lug) were left on site when the AR was released. After downloading, each AR was re-rigged with a new lug and anchor and redeployed. The flat anchor design was developed to allow trawls to skip

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over the anchor and receiver. A glass buoy was also used because it could not be punctured by trawl gear once it was recognized that trawl chains could puncture the original rubber buoys deployed.

The type of transmitters/tags most often detected in this study were Vemco®, V-16s. Though some (Wingate and Secor 2007, Kilfoil et al. 2017) have detected these largest of the Vemco 69 Khz tags at distances up to 1400 m during trials, others have settled on 600 m based on short term test using surface based VR100 computers and VR2AR transceivers (Ingram et al. 2019). Using Vemco® V16 transmitters, Simpfendorfer et al. (2002) determined 600 m to be a maximum range not an average. Several researchers using different methods (Egli and Babcock 2004, Humston et al. 2005, Brooking et al. 2006) have agreed that the distance is around 500 m and because this distance is continually changing due to abiotic (Heapel et al. 2008, Simpfendorfer et al. 2008, Singh et al. 2009, Mathies et al. 2014, Huveneers et al. 2016) and biotic conditions like fouling (Heapel et al. 2008, Mathies et al. 2014), we felt 500 m is a more conservative estimate.

2.2 Data Analysis Methods

Telemetry produces three principal statistics over time: a count of tags detected, a count of the number of detections, and a count of how frequently a tag was detected. Tag counts reflect the number of subjects detected at a site during a given time, the number of detections at a station reflect how long individuals occupied a particular location, and percent occurrence shows population-level occupation by monitoring the proportion of the given time that any individual is detected at a receiver site. Traditionally, diet content studies contain strikingly similar counts: a numeric count, mass or volume count, and a count that reflects frequency of occurrence (Hyslop 1980). Pinkus et al. (1971) derived a way to combine these three variables through an indices of relative importance (IRI) that canceled out some of the inherent biases of each individual component and provided a standardized means of comparison. A single index also allows for development of advanced models that can produce correlations between occupation patterns and physical and environmental variables over time and space.

The diet IRI (Pinkus et al. 1971) is expressed as:

$$IRI = (\%N + \%M) * \%O$$

where,

% N is the summed count of a particular prey item out of the total number of prey items counted in all stomachs, % M is the percent of the summed mass of a particular prey item out of the mass of all prey items observed in all stomachs, and % O is the percent of stomachs containing a prey item.

The model we applied to our detection data is a similar analytical tool to the IRI (Pinkus et al. 1971, Cortes 1997) that establishes a site-specific index of relative importance (SIRI) based on the varied statistics detection data produces. Unlike the dietary approach that looks at numerous stomachs until a cumulative prey curve indicates that a sufficient number of stomachs have been examined to describe dietary variability (Ferry and Cailliet 1996, Cortes 1997), the SIRI divides detection data spatiotemporally. By examining detection statistics over different periods of time and space it is possible, given enough data, to determine spatial and temporal distributions. Identifying spatiotemporal patterns of distribution and the migration corridors that enable such alterations in distribution over time is a necessary component to protecting natural resources (Ingram et al. 2019, Rothermel et al. 2020, Hogan et al. 2023). Like the dietary IRI, the SIRI incorporates all the statistics derived from detection data into a single standard value for each passive receiver site that reduces the inherent bias of each detection-based component alone and provides a means of site comparisons within or between studies over time. Unlike stomach content, where different types of prey items congruently occur in a single stomach and these

items are often grouped based on taxonomy, detection data is discrete. Though different fish may be detected at the same time, all detections are of equal value. There is no potential for varied nesting approaches or unintentional overweighting of one type of detection versus another, thus the weaknesses in the Pinkus et al. (1971) IRI formula do not occur and thus there is no need to address them through modifications proposed by Brown et al. (2012).

Therefore, our SIRI approach is very similar to the simple original diet IRI proposed by Pinkus et al. (1971):

$$SIRI = (\%N + \%D) * \%O$$

where,

% N is the number of fish detected during a given time over the total detected over the entire period, % D is the percent of detections during that time over the entire period, and % O is the percent of times when a detection occurred during the given time over the entire period considered. For our purposes, %N is the number of unique transmitters detected at a site in a month divided by the total number of transmitters detected during a given year, % D is the number of detections at a given site during a given month divided by the sum of all detections at all stations annually, and % O is the number of days that contained detections in a given month divided by the number of days in a year. Because the final product of a SIRI or diet IRI can be numbers ranging from quite large to relatively small, Cortes (1997) recommends using the percent diet IRI as a more robust analysis. To attain % SIRIs monthly SIRI values were determined for each month in each year for all years containing complete monitoring (2016–2020). SIRI values per site for each month of the year were summed across years then divided by the sum of these averages to attain the average % SIRI per month. When these % SIRIs are summed across a given month, the relative importance of the region can be determined by month. If summed across a given site, one can compare the relative importance of each site during the study. Individually, each value in the site month matrix compares the average relative importance of each site across time and space.

We applied the % SIRI method because we wanted to compare the average relative importance of sites within the array over time and space. Averaging across the numerous years of data we collected played to the strength of our long-term data set and its inherent ability to minimize the bias introduced by short term alterations in spatiotemporal distributions due to inter-annual abiotic or biotic factors. Averaging also minimizes the effect of short-term biases that might have been introduced by the unusual biological attributes inherent to a few tagged individuals, which we lacked the meta-data on to account for in any other way. Averaging across multiple years to better understand periods of typical occupation also best suited the goal of mitigating impacts due to exploration and construction through spatiotemporal restrictions because it provided a better assessment of what typical occupation patterns were since outliers were moderated. Though comparing site-specific variables across varied scales of space and time, as others have done (Ingram et al. 2019, Rothermel et al. 2020), is highly valuable to understand how distributions are related to biotic and abiotic variables, it is outside the scope of this research effort.

3 Results

3.1 Deployment Results

The array was contracted to be deployed from December 2015 through December 2019 with each receiver site to be checked once every other month during the period. The period of the array's true deployment, because routine maintenance checks were postponed due to unsafe conditions and associated safety concerns, was from 12/16/15 until 6/6/20 for a total of 1634 days. Because the array was deployed in mid-December of 2015 and removed in very early June of 2020, every season was not monitored for the same amount of time. In fact, raw data is skewed towards detections resulting in the spring (**Table 1**). By removing data collected in years with incomplete monitoring from SIRI analysis we eliminated the bias that would have been introduced by uneven data distribution across seasons.

Table 1. Days of monitoring by month from 12/15/15 until 6/6/20 and corrected days so that monitoring was not biased by partial year data.

Month	Sampling Days	Percent of Total	Corrected Days	Corrected Percent
Jan	155	9.5	124	8.5
Feb	141	8.6	113	7.7
Mar	155	9.5	124	8.5
Apr	150	9.2	120	8.2
May	155	9.5	124	8.5
Jun	126	7.7	120	8.2
Jul	124	7.6	124	8.5
Aug	124	7.6	124	8.5
Sep	120	7.3	120	8.2
Oct	124	7.6	124	8.5
Nov	120	7.3	120	8.2
Dec	140	8.6	124	8.5
SUM	1,634	100.0	1,461	100.0

Receivers at individual sites were not deployed for the same amount of time at every site nor were they checked on the same dates. A few holes in the data occurred due to receiver loss and failure between maintenance dates. In some cases, these losses of data correlated with other activities in the region known to BOEM but not us. **Table 2** contains the dates of each site's visit in colors that identify temporal gaps in data which resulted in a different number of total days monitored at receiver sites 7, 8, and 9. Though only considering data from whole years eliminates the bias at site 9, it does not eliminate potential short term bias due to equipment failure at site 7 and 8.

Table 2. Maintenance dates of receiver sites.

BOEM 7	BOEM 8	BOEM 9	BOEM 10	BOEM 11	BOEM 12
12/16/2015	12/16/2015	12/16/2015	12/16/2015	12/16/2015	12/16/2015
3/9/2016	3/9/2016	3/9/2016	3/9/2016	3/9/2016	3/9/2016
5/8/2016	5/8/2016	5/8/2016	5/8/2016	5/8/2016	5/8/2016
6/29/2016	6/29/2016	6/29/2016	6/29/2016	6/29/2016	6/29/2016
8/26/2016	**8/26/2016**	8/26/2016	8/26/2016	8/26/2016	8/26/2016
11/2/2016	**11/2/2016**	10/19/2016	10/19/2016	10/19/2016	10/19/2016
12/21/2016	12/21/2016	12/21/2016	12/21/2016	12/21/2016	12/21/2016
3/9/2017	3/9/2017	3/9/2017	3/9/2017	3/9/2017	3/9/2017
5/16/2017	5/16/2017	5/16/2017	5/16/2017	5/16/2017	5/16/2017
7/18/2017	7/18/2017	7/18/2017	7/18/2017	7/18/2017	7/18/2017
10/10/2017	10/10/2017	10/10/2017	10/10/2017	10/10/2017	10/10/2017
12/17/2017	12/17/2017	12/17/2017	12/17/2017	12/17/2017	12/17/2017
2/20/2018	2/20/2018	2/20/2018	2/20/2018	2/20/2018	2/20/2018
4/14/2018	4/14/2018	4/14/2018	4/14/2018	4/14/2018	4/14/2018
6/14/2018	6/14/2018	6/14/2018	6/14/2018	6/14/2018	6/14/2018
7/29/2018	7/29/2018	7/29/2018	7/29/2018	7/29/2018	7/29/2018
10/15/2018	**10/15/2018**	10/15/2018	10/15/2018	10/15/2018	10/15/2018
12/13/2018	**12/13/2018**	12/13/2018	12/13/2018	12/13/2018	12/13/2018
2/26/2019	2/26/2019	2/26/2019	2/26/2019	2/26/2019	2/26/2019
6/17/2019	6/17/2019	6/17/2019	6/17/2019	6/17/2019	6/17/2019
8/20/2019	8/20/2019	8/20/2019	8/20/2019	8/20/2019	8/20/2019
10/25/2019	10/25/2019	10/25/2019	10/25/2019	10/25/2019	10/25/2019
12/16/2019	12/16/2019	12/16/2019	12/16/2019	12/16/2019	12/16/2019
4/17/2020	4/17/2020	**4/17/2020**	4/17/2020	4/17/2020	4/17/2020
6/6/2020	6/6/2020	**6/6/2020**	6/6/2020	6/6/2020	6/6/2020
1559	1508	1584	1634	1634	1634

The first white row indicates deployment date, gray cells indicates periods of uninterrupted data, red cells with bold text indicates data missing, and the bottom row is the total number of days with monitoring.

3.2 Species Specific Detection Data

Twenty-four unique species were detected in the array in the 1,634 days of monitoring. Five species occurred at numbers of 20 or more individuals (**Table 3**) and their presence over time was examined more closely in later sections. The SIRI approach was only applied to Atlantic sturgeon because it was the only ESA-listed species detected. These results are presented in the following species' section. The remaining seventeen species did not occur in large enough numbers to warrant such detailed analysis; however, data is not without value and is presented in summary below (**Table 3**) and in total in **Appendix B** to provide guidance.

Table 3. The three types of detection statistics: number of individuals, total detections, and number of days with detections (out of 1,634 days monitored) are presented by species.

Species	Individuals	Detections	Days
Atlantic sturgeon	393	13321	447
Sand tiger shark	91	4461	118
Cobia	71	5351	124
Unknown	29	932	32
Blacktip shark	22	1688	44
White shark	21	512	29
Dusky shark	12	348	10
Sandbar shark	11	172	10
Cownose ray	9	156	10
Striped bass	6	141	6
Tarpon	4	59	6
Common thresher shark	3	137	3
Spiny dogfish	3	33	3
Atlantic angel shark	2	404	2
Spotted sea trout	2	21	2
Tiger shark	2	78	3
American shad	1	8	1
Atlantic bluefin tuna	1	32	1
Black drum	1	1	1
Bull shark	1	7	4
Finetooth shark	1	88	3
Little skate	1	25	1
Spinner shark	1	13	1
Winter skate	1	2810	6

As stated previously, knowing the biologically significant metadata related to each tag is integral to interpreting detection data. For example, though we know that most sturgeon carrying tags are adults because only adults and large sub-adult use shelf habitats, we know almost nothing else. To better understand detection data in the future, it will be necessary to incorporate and then properly sub-set detection data based on biologically significant attributes of each tagged individual. Information on the researchers who tagged detected fish are given by species in **Appendix C** to enable this much more beneficial approach in the future.

3.2.1   Atlantic sturgeon (*Acipenser oxyrinchus oxyrinchus*)

The number of endangered Atlantic sturgeon detected and the number of total detections resulting from these individuals was an order of magnitude greater than the next most commonly detected species (**Table 3**). The total number of sturgeon detected in the region was also surprisingly consistent across years with complete monitoring (2016–2019), as was the total number of days with detections (**Table 4**). The smallest number of individuals in a year was 109 (2019), and the largest was 134 (2017). The number of total days per year only varied from 96 (2018) to 103 (2017). Examining regional detection data across

the entire sample period by month (**Table 5**) clearly identifies consistent apexes in all three detection statistics in the months of April and November and an absence of detections in July and August, which correspond to known regional shelf migration and estuarine occupation periods (Hager 2011, Hager 2019). The raw detection data on Atlantic sturgeon by month and year (**Appendix D.1**) and by receiver site, month and year (**Appendix D.2**) is presented in **Appendix D** to provide a basis for further analysis.

Table 4. The annual number of Atlantic sturgeon, detections, and the number of days with detections are listed.

Species	Year	Individuals	Detections	Days
Atlantic sturgeon	2015	7	123	6
Atlantic sturgeon	2016	126	3,163	99
Atlantic sturgeon	2017	134	3,300	103
Atlantic sturgeon	2018	110	2,431	96
Atlantic sturgeon	2019	109	3,479	100
Atlantic sturgeon	2020	42	825	43

Table 5. The total number of Atlantic sturgeon, detections, and the number of days with detections in Sandbridge Lease Area are presented by month.

Month	Individuals	Detections	Days/Month
Jan	46	1,105	36
Feb	33	1,035	33
Mar	73	1,479	62
Apr	111	3,227	87
May	50	951	50
Jun	7	45	7
Jul	0	0	0
Aug	0	0	0
Sep	4	135	5
Oct	23	446	23
Nov	143	2,997	81
Dec	89	1,901	63
Total	579	13,321	447

Graphing regional detection statistics over time (**Figure 2**) illustrates how these indicators of occupancy fluctuate over time with temperature. The mathematical relationship between detection statistics is indicative of temporal occupation patterns that imply behavior. Although no mathematically significant correlation between a specific temperature and sturgeon abundance in the region was statistically explored, increased abundance during known periods of sturgeon migration during the spring (April) and fall (November) occur when temperatures are fluctuating rapidly. The absence of detections in July and August and very low numbers in September correspond to periods of high estuarine occupancy and spawning by adults in the Chesapeake Bay region (Balazik et al. 2012, Hager et al. 2014, Hager et al 2020).
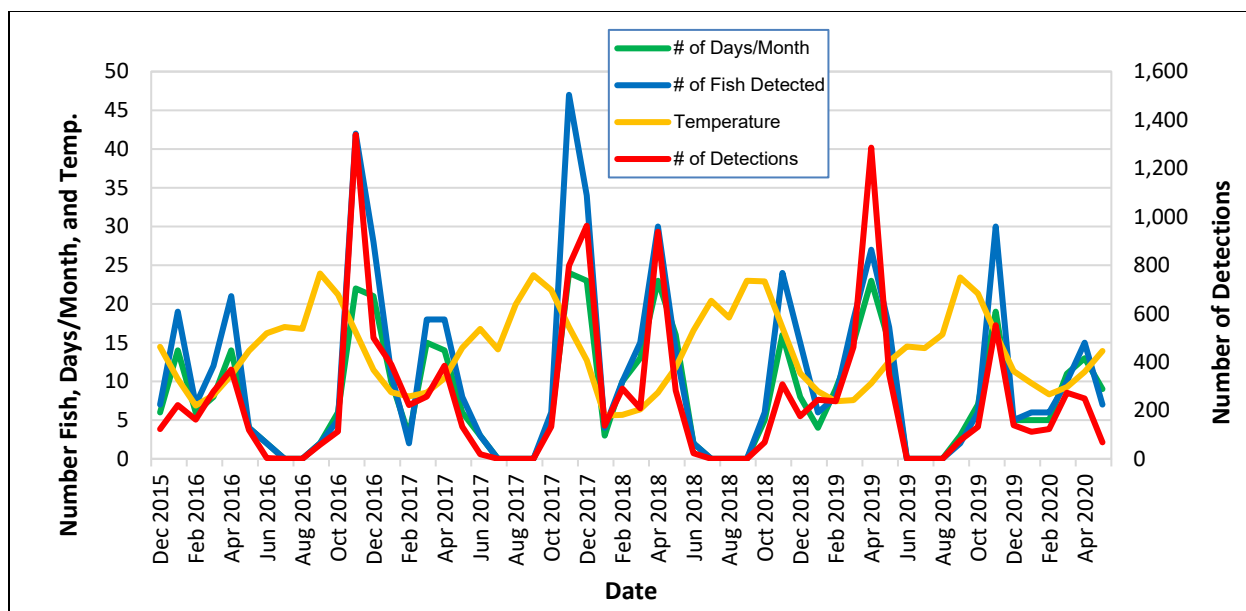
Figure 2. Regional Atlantic sturgeon detection statistics are graphed with temperature.

The gridded design of SBA receiver sites was selected, in part, in hopes that the direction of movement within the grid could be determined. Unfortunately, the detections in the SBA were too limited to effectively achieve this. To examine seasonal direction of travel through the SBA, we used data on York River sturgeon only. This was done because we possess the important metadata on these fish, such as life stage, sex, and natal origin, factors that affect behavior and movement and so provide the basis for improved interpretation of results. These fish also provided an additional advantage in that they are all adults from the same river in the Chesapeake Bay, and thus the majority return to their natal river to spawn each fall (Hager et al. 2020). Therefore, if detected in the SBA in order to return to their native river, these fish had to pass through three arrays: the cable region array (CRA) deployed to the north along the potential wind farm's cable line, the USN array in the Chesapeake, and finally the private York River array run by CS. This significantly increased the odds that they would be detected, and thus the direction of travel able to be determined.

Of the 46 events in which York River tags were detected, 24 were moving south in the fall, and 5 were moving north in the spring. No direction was determined for the remaining 17 events. The sex of fish varied during migrations and did not influence the direction of movement. Of the 24 fish moving south in the fall, 9 were female, and 15 were male. Of the fish moving north in the spring, 3 were female and 2 were male. These numbers would mean very little except that tags were evenly distributed between the sexes by the end of 2019 and thus the likelihood of detecting a tag of either sex should be roughly equal. Results may also suggest that sturgeon are more likely to be found along the southern coast at this latitude and distance from shore during fall migrations south than spring migrations north.

The SIRI results (**Table 7**) examine each receiver site's relative importance over time (month) and space (receiver site). As previously mentioned, to address the biases inherent to our raw data introduced by unequal monitoring across seasons, only years with complete seasonal monitoring were included in the SIRI. This approach eliminated bias at site 9, but data loss at site 7 (winter of 2018–2019) and at 8 (fall 2018) though minor could have potentially reduced the relative importance of these sites (**Table 2**). Summing across the SIRI matrix horizontally provides comparisons among sites over time based on their average SIRI across years. Summing vertically provides a relative comparison between months as an indicator of the region's temporal importance. Based on an assumption that each site is equal in its

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relative importance across time and space, each cell within the matrix should have a % SIRI value equal to 100 divided by the number of cells (n = 72) or in this case 1.39. To help further illustrate comparisons between SIRI values, values that are higher than the average SIRI value based on an even distribution of fish over time and space are in bold and shaded. The large values in April and November are indicative of the large numbers of fish migrating through the region at these times. The larger SIRI values across an elongated period in November and December suggests that the fall migration which consists of more fish is prolonged in duration in comparison to the spring.

Table 7. SIRI output (as a percentage), based on site-specific detection data.

Receiver Site	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Site % SIRIs
BOEM 7	1.1	0.6	**1.5**	**10.4**	**2.0**	0.1	0.0	0.0	0.0	0.1	**4.0**	**1.7**	21.5
BOEM 8	0.5	0.6	0.8	0.8	0.6	0.0	0.0	0.0	0.0	0.0	**3.0**	**1.7**	7.9
BOEM 9	0.5	0.5	0.8	**4.6**	0.8	0.0	0.0	0.0	0.0	0.3	**9.4**	**3.7**	20.6
BOEM 10	0.5	0.5	1.2	**6.4**	0.5	0.0	0.0	0.0	0.0	0.5	**6.3**	**2.9**	18.7
BOEM 11	0.7	0.6	**1.8**	**4.3**	1.1	0.0	0.0	0.0	0.0	0.4	**8.4**	**3.6**	21.0
BOEM 12	0.2	0.3	1.4	**1.7**	0.5	0.0	0.0	0.0	0.1	0.1	**4.0**	**2.2**	10.3
Monthly	3.4	3.0	7.5	28.2	5.5	0.1	0.0	0.0	0.1	1.4	35.2	15.7	100.0

Grey cells with bold values are larger than the average value of each assuming, equal detection distributions over time and space.

The six sites in the SBA region are relatively close to one another, thus little difference was expected between specific locations over time. The nearly equal SIRI values determined for the BOEM 7, 9, 10, and 11 sites suggest these sites are nearly equal in their relative annual importance. The lower values at BOEM 12 and BOEM 8 that are essentially half those determined for the other four sites suggest these locations are less occupied. The assumption that detection data can be used to determine occupancy and increased occupancy conveys preference is a principle assumption of the value of detection data. Though the BOEM 7 site appears preferred in the spring, it is of comparatively less importance in the fall. The preference for the BOEM 7 site in the spring is interesting because it is not only the closest site to shore but is also located in a deeper slough running north to south parallel to shore. Our results suggest the region is most important as a migration corridor and appears to also suggest that it is of greatest relative importance during the fall migration south.

Based on % SIRI results, it appears that the BOEM 7, 9, 10, and 11 sites hold near equal significance regionally and essentially during the same months. The BOEM 12 and BOEM 8 sites appear to have less relative importance regionally but are still of greatest importance during migration periods particularly the fall. Near equal relative importance between sites is likely largely due to the close geographical proximity of the sites and their similarity in terms of habitat. Of potentially notable exception, sturgeon exhibit a preference for the BOEM 7 site during the spring season that they do not in the fall.

3.2.2   Sand tiger shark (*Odontaspis taurus*)

The sand tiger shark (*Odontaspis taurus*) was the second most common fish detected in the SBA (**Table 3**). The total number of sand tiger detected in the region was not consistent across years with complete monitoring (2016–2019) nor were the total number of detections or days with detections (**Table 8**). The smallest number of individuals per year was 14 (2016) and the largest was 38 (2018). The number of total days with detections within a given year varied from 13 (2016) to 36 (2018). Regional detection data by month across the entire sample period (**Table 9**) clearly identifies that the species was detected only from April through November, with apexes in all three detection-based statistics in the months of May and October, coinciding with seasonal migrations through the region. Increased detection numbers resulting

from fewer sharks over a reduced amount of time may suggest that a behavioral change during warm water conditions was indicative of searching for prey in the region rather than migrating through it. The complete regional detection data on sand tiger by month and year (**Appendix D.3**) and by site, month, and year (**Appendix D.4**) is presented in Appendix D.

Table 8. The annual number of individual sand tiger shark, total detections, and the number of days are presented.

Species	Year	Individuals	Detections	Days/Year
Sand tiger shark	2016	14	359	13
Sand tiger shark	2017	28	519	28
Sand tiger shark	2018	38	2,258	36
Sand tiger shark	2019	27	917	27
Sand tiger shark	2020	15	408	14

Table 9. The total number of individual sand tiger shark, detections, and the number of days with detections are listed by month.

Month	Individuals	Detections	Days
Jan	0	0	0
Feb	0	0	0
Mar	0	0	0
Apr	4	140	4
May	44	640	39
Jun	18	525	15
Jul	3	59	3
Aug	2	322	3
Sep	3	957	5
Oct	38	972	31
Nov	19	829	18
Dec	0	0	0
Sum	131	4,444	118

3.2.3 Cobia (*Rachycentron canadum*)

The number of cobia (*Rachycentron canadum*) detected in the region was very inconsistent across years (**Table 10**). The total absence of detections before 2017 is explained by the fact that no cobia were recorded as being tagged in the Atlantic Coast Tag data base (ACT) before this year. However, annual variability in detection statistics after 2016 is indicative of a species that does not show strong annual site fidelity. For example, in 2017, there was an average of 109 detections per fish, 46 per fish in 2018, 62 per fish in 2019 and, 19 per fish in 2020. Though site fidelity is not strong, the regional detection data across the entire sample period by month (**Table 11**) clearly identifies apexes in all three detection-based statistics (i.e., individuals, detections, and days) in the warm water months of September and early October and an absence of detections in all cool water months. The regional detection data on cobia by month and year (**Appendix D.5**) and by site, month, and year (**Appendix D.6**) are presented in Appendix D.

Table10. The annual number of individual cobia, detections, and the number of days with detections per year are presented.

Species	Year	Individuals	Detections	Days/Year
Cobia	2017	4	436	13
Cobia	2018	32	1,485	39
Cobia	2019	54	3,372	70
Cobia	2020	3	58	2

Table 11. The total number of individual cobia, detections, and number of days with detections are listed by month.

Month	Individuals	Detections	Days
Jan	0	0	0
Feb	0	0	0
Mar	0	0	0
Apr	0	0	0
May	11	154	9
Jun	15	486	13
Jul	9	199	16
Aug	14	786	25
Sep	39	1,759	25
Oct	44	1,967	36
Nov	0	0	0
Dec	0	0	0
Sum	132	5,351	124

3.2.4 Blacktip shark (*Carcharhinus limbatus*)

In total, 22 blacktip sharks (*Carcharhinus limbatus*) were detected during the sampling period (**Table 3**). The largest number of individuals detected was in 2019, but the greatest number of detections occurred in 2018 (**Table 12**). Examining the detection data by month shows a peak in October, with 13 individuals detected 975 times in 13 days. There were no detections from November through May (**Table 13**), which clearly identifies the species as warm-water dependent. When data is examined by month and year (**Appendix D.7**), the largest number of the species detected consistently occurs in October. However, the maximum number of blacktip sharks detected in any given October across all years is only 5. The regional detection data on blacktip shark (**Appendix D.7**) and site-specific data by month and year (**Appendix D.8**) are in Appendix D.

Table 12. The annual number of individual blacktip shark, detections, and the number of days with detections are presented.

Species	Year	Individuals	Detections	Days/Year
Blacktip shark	2016	2	33	2
Blacktip shark	2017	7	232	7
Blacktip shark	2018	7	910	15
Blacktip shark	2019	12	513	20

Table 13. The total number of individual blacktip shark, detections, and the number of days with detections are listed by month.

Month	Individuals	Detections	Days
Jan	0	0	0
Feb	0	0	0
Mar	0	0	0
Apr	0	0	0
May	0	0	0
Jun	7	215	12
Jul	5	107	6
Aug	5	199	6
Sep	6	192	7
Oct	13	975	13
Nov	0	0	0
Dec	0	0	0
Sum	36	1,688	44

3.2.5 White shark (*Carcharodon carcharias*)

In the SBA, 21 individual white shark (*Carcharodon carcharias*) were detected over the project period (**Table 3**). The number of sharks detected varied little by year and was consistently small. The largest number detected in a single year occurred in 2017, with only 7 (**Table 14**). A comparatively large number of all three detection statistics in April and November suggests that seasonal migrations through the region occur during these months (**Table 15**). The complete detection data on the species by year and month (**Appendix D.9**) and by site, month, and year (**Appendix D.10**) is presented in Appendix D.

Table 14. The annual number of white shark, detections, and the number of days with detections are presented.

Species	Year	Individuals	Detections	Days/Year
White shark	2016	6	126	7
White shark	2017	6	179	6
White shark	2018	7	101	7
White shark	2019	5	81	6
White shark	2020	3	25	3

Table 15. The total number of white shark, detections, and the number of days with detections are listed by month.

Month	Individuals	Detections	Days
Jan	0	0	0
Feb	1	49	1
Mar	2	32	2
Apr	5	54	5
May	3	57	3
Jun	2	33	2
Jul	0	0	0
Aug	1	36	1
Sep	0	0	0
Oct	4	79	5
Nov	6	156	7
Dec	3	16	3
Sum	27	512	29

4   Discussion

Movement, regardless of its temporal scale, is a fundamental biological process that affects a population's spatial, demographic, and genetic structure (Hays et al. 2016, Wittemyer et al. 2019). Therefore, understanding the spatiotemporal occurrence of marine animals is critical for assessment, management, and conservation (Pittman and McAlpine 2001, Lennox et al. 2019). Acoustic telemetry can provide insights into previously undiscovered aspects of movement over varied time scales (Hussey et al. 2015, Lowerre-Barbieri et al. 2021) by providing large volumes of presence/absence data over extended periods (Donaldson et al. 2014, Hidalgo et al. 2016).

According to the data we collected and accessed, the marine minerals lease area is not unique in its provision of habitat or its species occupation patterns. In general, with some exceptions to be discussed by species, the SBA appears to be very similar in its occupation patterns to other sites located a similar distance from shore that contain similar sand habitats located in the CRA and even in other BOEM receiver sites in WEAs further north (Ingram et al. 2017, Hager 2019, Rothermel et al. 2020, Hager and Breault 2023), which are most important as migration "flyways" (Rothermel et al. 2020) rather than foraging or overwintering habitats. This is in stark contrast to the extended overwintering residence illustrated by sturgeon in soft bottom depressions (Hager and Breault 2023) within the Wind Farm Array (WFA), presented in Volume 2 of this report.

4.1   Atlantic sturgeon (*Acipenser oxyrinchus oxyrinchus*)

When the Atlantic sturgeon (*Acipenser oxyrinchus oxyrinchus*) was listed under the ESA on 12 February 2012 (NMFS 2012a, 2012b) by the National Marine Fisheries Service (NMFS), its populations were divided into DPS based upon genetic similarities within geographically relevant areas. The DPSs were the Gulf of Maine, New York Bight, Chesapeake Bay, Carolina, and South Atlantic. All DPSs were listed as endangered except the Gulf of Maine, which was listed as threatened (NMFS 2012a, 2012b). While the DPSs are discrete entities, individuals belonging to each may range widely, migrating long distances across the shelf in order to find optimal temperatures and forage resources (Gross et al. 1988, Dingle and Drake 2007), which results in significant overlap with individuals from other DPSs in preferred locations. The areas of greatest overlap will be the areas of greatest non-reproductive importance, such as migration corridors and foraging and overwintering habitats. Atlantic sturgeon are already at risk from a variety of anthropogenic threats (ASMF 2009). Many researchers have concluded that due to slow growth and late maturity (sometimes over 25 years) even relatively low rates of mortality can cause declines in the abundance of a DPS (Boreman 1997, Secor and Waldman 1999, Gross et al. 2002). Therefore, it is imperative that we identify each DPS's preferred migration routes, foraging habitats, and aggregation areas in order to enable their recovery.

Our knowledge about Atlantic sturgeon has greatly expanded since listing in 2012, but scientific advancements within the Chesapeake Bay region have been exceptionally prolific. For over ten years a mark recapture tracking study has occurred in the York River system. During this time approximately 20 percent of its small adult population (~ n = 600, Kahn and Hager, unpublished data) has been acoustically tagged and important biological data obtained. Though no population assessments have been done on either of the James River's distinct genetic populations (one reproducing in the spring and one in the fall (White et al. 2021), it took over 12 years to identify that there was a spring population. Thus, catch records support the theory that it is also small (Balazik, ERDC, personal communication). Because smaller populations are at greater risk of extinction (Mace and Lande 1991, Frankham 1995, Lande 1998), it is necessary to define how small populations are and clarify their spatiotemporal distributions and critical habitats in order to preferentially minimize our negative impacts on them.

Before research funded by the USN and BOEM, most distribution data relied on commercial catch records and falsely identified the species as a nearshore winter resident (Stein et al. 2005). During our monitoring of the SBA, Atlantic sturgeon were the most frequently detected species, with the largest number of individuals and detections. Detection statistics suggest the SBA region is used primarily as a migration corridor which appears to be of slightly greater importance in the fall than in the spring (**Figure 2, Table 7**).

By applying the metadata on York River fish, we were able to determine that no significant difference in the sex ratios of adult fish from this population was evidenced during migrations. By combining detection data from the SBA, USN array at the bay's mouth (Hager 2019), and the BOEM CRA (Hager and Breault 2023) located north of the SBA, we were able to determine that adult sturgeon were moving south in the fall after emigrating out of the bay and north in the spring before they immigrate into the York River to spawn. Migrations were recorded when water temperatures were falling in the fall and rising in the spring (**Figure 2**), but more analysis will be required to determine what motivates these migrations and what biological factors may be linked to divergent approaches. Tracking data appears to suggest that physiological tolerances may depend on the genetics inherent to each DPS (Taylor et al. 2016, Hylton et al. 2018). Other research suggests that not only DPS but also sex influence the timing and chosen "flyways" of migrations, which result in varied spatiotemporal distribution patterns and the selection of critical habitats that are inseparably linked to fitness and spawning success. Clearly, there is a great deal more research needed to tease out which shelf habitats are critical to which individuals of which populations.

The % SIRI analysis suggests that the SBA region is most important to sturgeon as a seasonal migration corridor (**Table 7**). This finding agrees with other researchers who have tracked sturgeon in sites located at similar distances from shore with similar sand habitats (Ingram et al. 2017, Hager 2019, Rothermel et al. 2020, Hager and Breault 2023). The fact that the shallowest site in the SBA, BOEM 8, was selected against during both migration periods is interesting, given past literature that cites that sturgeon prefer the deepest location within a given region (Moser and Ross 1995, Bain et al. 2000, Savoy and Pacileo 2003, Musick and Hager 2007, Hager 2011). Numerous characteristics inherent to the BOEM 7 site likely make it a preferred route during spring migrations north. First, it was the SBA site located closest to shore. This is a trait it has in common with the CRA sites with the greatest relative importance during spring migration which were located closest to shore. It is also interesting to note that the BOEM 7 site is located in a relatively deep trough that runs parallel to shore, thus providing a deep path between south and north. The BOEM 7 site, therefore, may have characteristics that increase its occupancy during spring migrations.

4.2   Sand Tiger Shark (*Carcharias taurus*)

The sand tiger shark (*Carcharias taurus*) was the second most common fish detected. This large coastal shark (Compagno 1984) is a lamniform or mackerel shark in the family of Odontaspididae. Similar to the white shark, the sand tiger is highly migratory (Haulsee et al. 2018). Also comparable to the white shark, sand tigers range broadly in the Western North Atlantic Ocean from Maine to the Gulf of Mexico (Kneebone et al. 2012). As the lack of detection data in the offshore WFA suggests (Hager and Breault 2023), the sand tiger inhabits primarily shallow coastal waters (Compagno 1984) where it preys on bony fishes, small sharks and rays, and crustaceans. They are more active at night and can be found as lone individuals or in aggregates (Compagno 1984, Haulsee et al. 2018).

Like most of the other species that we examined in more detail, the sand tiger is a temporal resident with distinct migratory behavior moving north in the spring and south in the late fall (Haulsee et al. 2018). Our detection data illustrate that the sand tiger is in residence regionally in the SBA from April to November. Interestingly, though the CRA was not very far to the north of the SBA, the species did not show up in the

CRA until May. This slow movement north may suggest that the species in actively foraging while migrating. The species numbers were notably impoverished in both the CRA and SBA in July and August, when literature suggests the species aggregates around nearshore wrecks and at the mouths of bays where it preys primarily on sandbar sharks (Compagno 1984, Haulsee et al. 2018) that use the bay as pupping grounds and are abundant at this time (Murdy et al. 1997).

The sand tiger is known to pup around the barrier islands of Virginia's Eastern shore (Murdy et al. 1997), and many sand tigers migrate further north. Virtually no research has been done on young of the year or small juveniles, so it remains unclear as to how these life stages depend upon or migrate across shelf habitats. Similar to other lamniform sharks, in utero, the largest pups will eat the other smaller pups and/or eggs. Female sand tiger sharks have two uteri, resulting in two pups being born, one from each uterus (Compagno 1984). Sand tiger sharks have a gestation period of an estimated 8 to 9 months (Compagno 1984). Pups are born every two years and have a late reproductive age, resulting in a low fecundity, putting sand tiger sharks at a high risk of overexploitation (Teter et al. 2015).

The sand tiger shark is recorded in fisheries data as bycatch and commercial harvest. Since the mid-1970s, population declines for the sand tiger shark have been estimated to reach 80% to 90% (Kneebone et al. 2012). In 1997, NMFS made harvesting sand tiger sharks illegal (Kneebone et al. 2012, Teter et al. 2015). However, because a good population assessment does not exist for this species, quantifying if the shark's population has recovered at all is difficult. Sand tiger sharks are currently listed as vulnerable in Federal waters (Haulsee et al. 2018, Teter et al. 2015).

4.3   Cobia (*Rachycentron canadum*)

Cobia (*Rachycentron canadum*) is of considerable recreational importance in Virginia. In the past few years, its popularity as a sports fish and its subsequent landings have expanded significantly (Jensen and Graves 2020). Congruently, increased concerns regarding potential overharvest predicated primarily on a lack of movement and habitat utilization data necessary for sufficient management have arisen. Genetic evidence of distinct subpopulations and spawning site fidelity within stock management units (Darden et al. 2014, Perkinson et al. 2019) has augmented concerns that increased harvest pressures and habitat alterations in one location will have disproportionate consequences for certain subpopulations.

The cobia is the only member of the family Rachycentridae and is distributed worldwide in warm tropical and temperate coastal waters (Shaffer and Nakamura 1989). Along the east coast of North America, its range extends from Massachusetts to Argentina with residents in the Gulf of America and the Caribbean. Cobia supports a major recreational fishery throughout its U.S. Atlantic and Gulf of America (previously Gulf of Mexico) range (SEDAR 2013). It is attractive to anglers because it is larger than most inshore fish, is aggressive, and is often found in the surface eddies created by anthropogenic structures. Thus, it offers a unique visual fishing experience to mid-Atlantic anglers.

The temporal nature of our detections in the SBA agrees with our findings in the CRA and WFA (Hager and Breault 2023) and confirm (**Table 10**) as others have found (Murdy et al. 1997) that cobia are seasonal warm water visitors to Virginia arriving in the Chesapeake Bay in May and staying into October. Though often found solitary in the mid-summer during pre- and post-migration periods, it can sometimes be found in aggregation. We identified aggregations of cobia using detection data as being indicated by more than 10 individuals being detected more than 100 times for at least 10 days in a single month. This set of detection standards occurred across numerous SBA sites in September 2019 and at one site through October. This behavior was also recorded at the same time at the BOEM 1, RA, and CB sites located along a similar longitude in the CRA in September of 2019. These aggregations in 2019 may indicate spawning since it occurs during spring and summer (Lefebvre and Denson 2012) along the continental shelf (Hassler and Rainville 1975) or these late summer aggregations may be fish staging to depart to

overwinter in the offshore waters of North Carolina near the continental shelf break (Perkinson et al. 2019, Jensen and Graves 2020).

4.4 Blacktip Shark (*Carcharhinus limbatus*)

The blacktip shark (*Carcharhinus limbatus*), was the fourth most commonly detected species in the SBA. It is a tropical and subtropical species found worldwide nearshore and on the continental shelf (Castro 1996, Rigby et al. 2021). It is a requiem shark of the Carcharhinidae family and the order Carchariniformes. Their diet consists primarily of small bony fishes, and some small elasmobranchs. Like the other requiem sharks, blacktip sharks are viviparous and have embryonic development within the mother. After a 10–12 month gestation period, a female blacktip will give birth to an average of 4 to 6 pups at one time every two years (Castro 1996). One important nursery used by blacktips is on the U.S. East Coast in Bulls Bay along the coast of South Carolina (Keeney et al. 2003).

Blacktip shark have distinct population segments based on geographical location, which influence maximum size and life history (Castro 1996). Along U.S. shorelines they range from Massachusetts to Texas, with two distinct populations in the south Atlantic, one along the southeastern continental shelf of the U.S. and the other in the Gulf of Mexico (Carlson et al. 2006). Though the blacktip is native from New England to the Gulf of Mexico, it is rare to find them north of Cape Hatteras, North Carolina (Castro 1996). It is a seasonal visitor to Virginia's coastal waters and is most often found along coastal beaches and lagoons, which by default makes the bay's barrier islands preferred habitat. The Atlantic population on the U.S. East Coast migrates south to Florida during winter (Castro 1996, Keeney et al. 2003). Like all the other sharks we detected, it undertakes seasonal migrations along the shelf moving north as waters warm and south as they cool.

Blacktips mate in early spring or summer and give birth the next early summer in shallow coastal nurseries of the Carolinas and Georgia that provide suitable protection from predators and a reliable food source. The young will stay in the protection of shallow nurseries until fall (Castro 1996). It could be that because they mate in early spring and give birth in the summer, the SBA may contain nursery habitats for juvenile sharks, as several individuals were repeat visitors from year to year. This assumption is supported by previous research that suggests that blacktips are philopatric, returning to the same sites in order to deliver pups within suitable nursery areas (Rigby et al. 2021). Once again, without metadata on tagged individuals, such as life stage, our ability to interpret blacktip behavior through our detection data is severely limited.

Blacktip sharks are the fourth most harvested shark in the U.S., providing recreational value in the Atlantic population. Within recent years, the low end of blacktips caught and released was almost 100,000 in 2016, and the high end of almost 600,000 in 2015. Only 1% of blacktip caught in the Atlantic population were harvested, with about 8% harvested in the Gulf of America (previously Gulf of Mexico) (NMFS 2021). Blacktips are a species of interest for research and conservation due to their migratory patterns, distinct population segments, threatened International Union for Conservation of Nature listing, and their value as a commercial and recreational species.

The results of this study support the migration patterns of blacktip sharks cited in the literature. Because blacktip sharks are rarely found beyond North Carolina, it makes sense that we did not detect two distinguishable migrations through the SBA but rather one as they arrived for summer residence. After using shelf habitats like the SBA as a summer feeding ground, they departed in October. However, with a sample size of 22 individuals, it is very difficult to assert that our data characterizes the species true occupation patterns especially if spatiotemporal distributions are influenced by life stage which they most likely are.

4.5   White shark (*Carcharodon carcharias*)

The white shark (*Carcharodon carcharias*) is a migratory apex predator found globally in temperate to sub-tropical waters (Compagno 1984, Franks et al. 2021). It has been reported from Newfoundland to Argentina along the western shore of the Atlantic, but it is rare in equatorial waters. It is one of the largest sharks and it has reached iconic stature through media productions. White sharks are lamniformes and members of the Lamnidae family (Compagno 1984). Seven regions have white sharks: Southern Africa, Australia and New Zealand, the Northwest Pacific, Northeast Pacific, Mediterranean, Southwest Atlantic, and the Western North Atlantic. While there is some genetic mixing, sharks in these regions form distinct groups possessing different movement and behavioral patterns and these groups may consist of genetically distinct populations (Franks et al. 2021). Different populations have varied life histories, reproductive cycles, and maximum sizes (Franks et al. 2021). It is therefore more appropriate to assess their migrations and spatiotemporal distributions based upon their natal population.

The mating behavior of the white sharks in the Western North Atlantic region still lacks research (Skomal et al. 2017, Verkamp et al. 2021). However, we know that white shark grow slowly (Natanson and Skomal 2014) and mature at advanced ages but this varies regionally and by sex (Skomal et al. 2017). For example, in the Western North Atlantic region the female of the species does not reach maturity until 26 years and males until 34 years (Skomal et al. 2017). Though little is known about preferred temperature range of the prey species consumed within nursery areas by young sharks (Curtis et al. 2018), an important summer nursery has recently been identified in the New York Bight (Franks et al. 2021, Skomal et al. 2017) and another important juvenile white shark overwintering site spans from northern North Carolina to South Carolina along the shelf (Curtis et al. 2018, Franks et al. 2021, James et al. 2021). After overwintering, the juveniles migrate north in late spring and early summer (Franks et al. 2021). Though our research on juvenile white shark distributions in the Western North Atlantic region remains impoverished, what has been done suggests they spend most of their time along the continental shelf (Curtis et al. 2018) as do the adults (Skomal et al. 2017). Thus the entire species is heavily dependent on continental shelf habitats for foraging and migration corridors (Curtis et al. 2018).

Most evidence still supports a generalist diet of demersal fish and invertebrates for juveniles and a preference for marine mammals (Casey and Pratt 1985) by adults. Along the Western North Atlantic, as the seal population has rebounded, adults appear to have begun to consume more pinnipeds and this new prey source has increased white shark fitness and thus its populations (Curtis et al. 2018, Skomal et al. 2017). When feeding on pinnipeds along the New England coasts in the summer, large white sharks are in close proximity to humans participating in recreational and commercial activities (Natanson and Skomal 2014). Large gaps in data and our fascination with the fish's ominous reputation have made it an easily marketable species for public outreach and financial participation in research efforts. This, coupled with its population expansion and now common sighting along the New England coast in the summer, have resulted in a massive increase in its public awareness and increased funding for acoustic research. In fact, there are townships in New England that now sponsor tagging and tracking efforts to learn about white sharks in their local waters in an effort to minimize risks to bathers (Kneebone, New England Aquarium, personal communication). This has significantly increased the number of tagged white shark and what we know about them.

White shark in the Western North Atlantic region were not as well studied as in other regions, which was in large part due to their reduced populations (Curtis et al. 2018, Franks et al. 2021), but with the population rebounding and increased public concern, more sharks are being tagged and tracked. Historically, as was the case with Atlantic sturgeon, most of what we knew about white sharks was based on fishing records (Skomal et al. 2017), accidental captures, and rare sampling opportunities (Verkamp et al. 2021). Before the development of sonic tracking, the semi-solitary existence of the species made it difficult to study and define its life history. In fact, we still know very little about the species'

reproduction and early life history. Occupation patterns of the species across their ontogeny are largely unknown (Curtis et al. 2018, Franks et al. 2021, James et al. 2021, Skomal et al. 2017) but understanding the movement patterns of white sharks across all age classes is vital for its conservation (Skomal et al. 2017). Our acoustic array data provides some of the first purely observation-based data on the species in shelf waters off of Virginia.

Though our SBA white shark sample size was very small (n= 21), the relatively larger number of individuals detected in the spring (April–May) and fall (October–November) are indicative of periods of known migration (Skomal et al. 2017). Comparisons between our WFA, CRA, and SBA data support the assertions that the species spends a substantial amount of time within all shelf habitats buts prefers the outer continental shelf, where it exhibits a consistent presence (Franks et al. 2021). Interestingly, though no individuals demonstrated site fidelity in the SBA, a few did show regional site fidelity between the CB and BOEM 5 sites (2020) in the CRA from June to August (Hager and Breault 2023). Though these preferred sites are along a similar longitude as the SBA, they are very different in their proximity to the Chesapeake Bay and are along the east-west migration corridor followed by many estuarine dependent prey species. The increased incidence of site fidelity by the white shark in these locations may suggest that this large predator may be more dependent upon estuarine resources than previously realized and, like many other large predators, which may not enter the estuaries, they are still trophically dependent on estuarine productivity.

White sharks are present in shelf habitats during every life phase. But because we lack the metadata that would indicate life stage, it is very difficult to support some assertions as to how detection data indicates behavior. However, animals do not waste energy so they remained in these sites because they were benefiting in some bioenergetic manner. Not knowing the age of tagged individuals also makes it impossible to determine if the increased numbers we see in the fall are juveniles on their way to overwintering sites along the Carolina shelf (Curtis et al. 2018, Franks et al. 2021, James et al. 2021) or adults on their way to the Gulf of Mexico for the winter (Franks et al. 2021, Skomal et al. 2017). A lack of data also affects our ability to interpret the spring through early summer migrations north that was documented in both of our inshore arrays, so, again, we do not know if these tagged individuals were juveniles on their way to nursery grounds in the New York Bight (Franks et al. 2021, Skomal et al. 2017) or adults bound for the New England coast to feed on marine mammals. And though we have many years of data, without access to life stage we are unable to examine our data to determine if white sharks become progressively more pelagic with age (Franks et al. 2021, Skomal et al. 2017).

Because different white shark life stages have unique characteristics concerning habitat occupancy and movement, white shark detections are more likely to consist of individuals with vastly different behaviors and patterns of movement. Larger fish like white sharks also swim at much greater speeds than small ones. Therefore, adult white sharks that are at least three times as large as an adult sturgeon and likely five times the size of a large blacktip would not remain within the detection distance of a receiver for long in comparison. Our array was not designed to track such large fast-moving fish. If one sums the number of fish detected across all years without regard to whether the individual had been detected before, that yields 27 total white sharks detected. Of these, 21 were unique individuals, leaving only 6 individuals that were repeatedly detected in five years. This suggests that either migration corridors were not consistent or that the area monitored was too small to adequately capture species migrations. However, this assertion is based on such a small number of the species of unknown life stages that no real conclusions can be drawn.

4.6 Concluding Remarks

Data from different sources over time suggest that the depths of receiver sites within the SBA are continually being altered over time. Anthropogenic manipulation of this important habitat component and

associated alterations in benthic communities due to sediment removal result in inconsistent habitat and trophic resource provision which likely alter site selectivity by different species to various degrees over distinct time periods. The original map that BOEM constructed before the project initiation cites the site's depth as varying from 8.7 to 17.6 m. Our data recorded that sites vary from 10.97 to 16.3 m and the lidar map we attained for **Figure 1** suggests still different depth values. This dynamic system has natural erosion and accretion. Naturally, because the sites are dredged for sand, some of the depths in the region are constantly being altered and may change more measurably every 3 to 5 years. Smith and Clungston (1997) and Van Dolah et al. (1984) speculated that dredging and filling can impact important habitat features of Atlantic sturgeon by disturbing benthic fauna, eliminating deep holes, and when in fresh water habitats depositing silt over rocky substrates used for spawning. Thus, disturbances due to dredges have ramifications but exactly how these alterations have affected our results is unknown. Because we have no data on the spatiotemporal parameters associated with dredging or the extent to which they altered the habitat in the SBA, we do not know if species behavior or regional occupation patterns were altered or if migrations were affected by these anthropogenic activities. Reine et al. (2014) suggest that Atlantic sturgeon do not respond to dredges in that they do not avoid them. So, though interactions are known to occur (Reine and Clarke 1998), how operations can be altered to minimize risks for this species remains unknown. Since our data illustrate that sturgeon are not equally distributed over time or space, spatiotemporal restrictions may be the most efficient way to minimize interactions with this ESA listed species. There is virtually no data on how the other four other species we focused on respond to dredges or how such activities may affect their trophic resources, though we are learning more (Reyier et al. 2023).

In fact, very little is known about most species' distributions while in the ocean, and even less is known about how our actions impact them. Our ability to understand shelf habitats is complicated further by the fact that contingents of the same species vary in their behavior, selection of foraging grounds, migration corridors, and overwintering habitats. Therefore, the habitats that may be considered critical to one population and/or contingent may not be to another even within the same species. These population or contingent based differences are of significant importance to this study because sturgeon (ASMFC 1998), cobia (Darden et al. 2014, Perkinson et al. 2019), blacktip (Castro 1996), and likely white shark (Franks et al. 2021) all consist of different populations with different and still poorly understood life histories and environmental requirements. Thus, alterations within yet unidentified critical habitats and/or migration corridors could have highly undesirable contingent specific consequences (Rothermel et al. 2020). Future tracking studies should not group all the detections of a species together but sub-set the data by any and all biological significant attributes recognized to affect habitat occupation.

This research is an important first step and is thus far one of the only acoustically based attempts to determine movements and spatiotemporal patterns of habitat occupation by various species on Virginia's continental shelf; however, its value is limited because it is based on presence/absence data alone. A more inclusive approach is deserved and possible given greater collaboration between researchers.

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Appendix A: SIRI Manuscript

A Site-Specific Detection Based Index of Relative Importance for Tracking Data

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Impact Statement

The site-specific index of relative importance (SIRI) provides a means of combining different detection-based data into a single, standardized value. This provides a means of comparing sites within and between studies based on habitat preference and expands the utility of telemetry data in more advanced models.

Abstract

A passive telemetry array records the temporal and spatial distribution of telemetered individuals in terms of presence and absence but there is no generally agreed upon method of analyzing those detections to objectively identify habitat preference. However, a statistical approach that derives an index of relative importance (IRI) has long been accepted in the trophic literature. Here, we propose and validate a similar analytical tool that establishes a site-specific index of relative importance (SIRI) based on detection data. It incorporates the number of subjects detected, how many detections occurred, and the frequency of site occupation into a single index. This produces a standard value for each passive receiver site that reduces the inherent bias of each detection-based component alone and provides a means of site comparisons within or between studies over time. A single index per site also allows for development of advanced models that can produce correlations between occupancy patterns and physical and environmental variables over time and space.

Introduction

The use of remote passive telemetry monitoring has become standard practice in examination of animal movement and habitat selection in recent years. This method relies on an array of passive/fixed receivers that detect the presence of acoustically telemetered individuals passing within a detectible distance. Over time the array records the temporal and spatial distribution of telemetered individuals. Telemetry has greatly expanded what we know about species distributions, both supporting and refuting our initial understanding of species' ecology based on limited mark recapture and/or harvest data (Stein et al. 2005, Thorstad et al. 2013, Cramer 2015, Ingram and Peterson 2016). While detection data have increased our understanding of habitat occupation and preference (Hatin et al. 2007, Aarts et al. 2008), there is not a simple metric for combining the different types of information collected by passive receiver arrays.

Many telemetry analyses rely on total detections per location (Hatin et al. 2007, Hale et al. 2016, Hollensead et al. 2018, Ingram et al. 2019, Secor et al. 2021), describe movement in terms of detections on a receiver on a particular day (Hatin et al. 2002, Koster et al. 2014, Hollensead et al. 2018, Ingram et al. 2019, Brownscombe et al. 2022), or frequency of detections/non-detections of individuals in a given location (Hatin et al. 2002, Reyier et al. 2014, Ingram and Peterson 2016, Ingram et al. 2019, Secor et al. 2021). Each of these metrics and others are useful for identifying habitat selection, habitat function, habitat connectivity, spatio-temporal habitat use or occupation, or multi-species habitat use (Brownscombe et al. 2022). As beneficial as those individual assessments can be, there is no means of standardizing the data in telemetry analyses, and therefore assessments in other times and places are generally not comparable to one another. Modeling techniques such as a habitat suitability index are quite useful and can effectively predict habitat usage (Verner et al. 1986, Morrison et al. 1992, Roloff and Kernohan 1999) but require considerable knowledge of fine-scale habitat composition, which can be challenging for aquatic species and even more so for wide-ranging aquatic species. Habitat suitability indices for aquatic species in passive arrays are also complicated by the presence of a variety of potentially preferential habitats within the detection radius around a receiver, often requiring analysis of spatially constant habitat variables such as flow, depth, temperature, or salinity (Wang et al. 2013, Yu et al. 2018, Rudolfsen et al. 2021). Likewise, kernel density estimates from passive arrays in open water (large estuaries and ocean) may be misleading (Reyier et al. 2014).

An emerging problem is standardizing telemetry detections across broad geographic regions to allow for broad-scale comparison (Udyawer et al. 2018). An index of relative importance (IRI) was developed and improved to promote consistency, reduce bias, and standardize statistical methodology of diet studies (Pinkas 1971, Bigg and Perez 1985, Brown et al. 2012) by producing a single value to describe the importance of each prey item. These prey items could then be compared easily, within a species, across species, and through time (Manooch and Mason 1983). There are important and useful parallels between diet preference studies and habitat preference studies.

Prior to the IRI, assessments of gut contents focused on qualitative descriptions of prey (Hartley 1948) or quantitative measures of prey counts, weight of prey, or frequency of occurrence, but not in a standardized way (Hynes 1950, Medin 1970). In diet analyses, each measure provides a

different insight into the feeding dynamics and trophic dependencies of the predator and provides independent value. Counts or numeric abundance provide insight into feeding behavior (MacDonald and Green 1983) and/or prey abundance/availability (Paltridge 2002). Mass or weight provides a means of measuring nutritional or bioenergetic value (MacDonald and Green 1983), and occurrence represents the relative importance of a prey item at the population level (Cailliet 1977).

The diet IRI (Pinkas 1971) is expressed as:

$$IRI = (\%N + \%M) * \%O$$

where, % N is the percent of the summed counts of a particular prey item out of the total number of prey items counted, % M is the percent of the summed mass of a particular prey item out of the mass of all prey items observed, and % O is the percent of stomachs containing a prey item. Telemetry, like gut content analyses, produces measures of counts that measure the number of subjects present at a station during a given time, the numbers of detections at a station reflect how long individuals used a particular location, and percent occurrence shows population-level occupation by monitoring the proportion of days any individual is detected at that station, which can be used to produce indices of relative importance, providing a standardized means of comparison.

The purpose of our study was to establish an index of relative importance for site specific telemetry data that can be used to compare spatiotemporal occupation patterns between receiver sites and the habitats they monitor. Based on the assumption that animals preferentially occupy habitats that increase their species' odds of survival, occupation patterns over time can be used as a surrogate for habitat preference. We compared our model with an accepted model for identifying habitat utilization to evaluate its product. Once measured in a standardized way, comparisons of preferences at regional and global scales can be made.

Methods

Model development. – A single passive receiver provides insight into species presence or absence, while an array provides insight into habitat occupation, movement, and site preference through time within a geographic area. Given a large enough receiver array in a geographic area over time, we are able to make inferences about habitat preferences by assessing each receiver site for the number of individuals detected, the number of detections, and the frequency at which individuals were detected. All three of these variables are valuable in describing a given location's occupation by telemetered individuals but in different ways. The first reflects how many transmitters were detected at a particular site in a given time period. The second records how long these subjects remained within detection distance, and the third the proportion of time periods a location was visited. Because a fish stomach is a finite unit and time is not, time must be standardized for this analysis. We used a one-day period. However, as long as the time period across which variables are considered is consistent, any time period can be used. In doing so, we create two matrices just as we do with gut contents, where one allows the summation of individuals per time period at each station and one allows the summation of detections per time period at each station, with percent occupation being calculable for each station using either

matrix:

$$
\text{Individuals detected in a day (j)} \quad
\begin{matrix}
& \text{Passive receiver stations (i)} \\
& \begin{bmatrix} x & x & x \\ x & x & x \\ x & x & x \end{bmatrix}
\end{matrix}
$$

and

$$
\text{Total detections in a day (j)} \quad
\begin{matrix}
& \text{Passive receiver stations (i)} \\
& \begin{bmatrix} x & x & x \\ x & x & x \\ x & x & x \end{bmatrix}
\end{matrix}
$$

Brown et al. (2012), proposed a modification to the diet IRI to account for prey-specific weights (%PSW) and counts (%PSN) being related to observed frequency (%O), leading to an over-emphasis of frequently occurring prey and an under-emphasis of the importance of rare prey (Brown et al. 2012). This approach helped address differences in the taxonomic levels of prey and/or different nesting of prey items by categories applied by various researchers that inhibited comparisons between diet content studies. This approach, however, is not necessary or appropriate for detection data. Detection data is discrete, thus there is no potential for varied nesting approaches or unintentional overweighting of one taxonomic level verse another. Our original SIRI approach thus remained simple like the diet IRI proposed by Pinkas (1971):

$$
\text{SIRI} = (\%N + \%D) * \% O
$$

where, % N is the percent of the number of fish detected during a given sub-period over the summed total detected over the entire period, % D is the percent of detections during the same sub-period over the sum across the entire period, and % O is the percent of sub-periods containing detections. For our purposes, N is the number of unique transmitters detected at a site each day divided by the total number of detections that occurred during the entire study period being considered, % D is the number of detections at each station each day divided by all detections at all stations, and % O is the percent of days containing detections.

Because receivers can be lost or fail during a study, we are still able to use the partial data collected during a study by modifying % O to represent the percent of time a transmitter is detected over the number of days that particular receiver was functional. Because the final product of a SIRI or diet IRI can be numbers ranging from quite large to relatively small, Cortes (1997) recommends using the percent diet IRI as a more robust analysis and we applied this approach as well.

Validation location and telemetry. – The York River, Virginia, located along the western edge of the Chesapeake Bay is known to contain a spawning population of Atlantic sturgeon (*Acipenser oxyrinchus oxyrinchus*) that return each fall (Hager et al. 2014). The receiver array examined in this study consisted of nine Vemco VR2W-69 kHz receivers in the York River and one in the Pamunkey River. This stretch of water transitions from polyhaline at the lowest York River

station to oligohaline, which is known to be important to pre- and post-spawn Atlantic sturgeon (Hatin et al. 2002, Ingram and Peterson 2016). Salinities are monitored within the river as part of the National Estuarine Research Reserve System (NERRS) at river kilometer (rkms) 11, 27, 39, and 74 (Table 1). The changes between monitoring stations was interpolated and presented as a range of salinities, caused by changing tides and flows, in the river throughout the study periods. Stations were established at rkms 11.3, 14, 20.3, 26.8, 36.8, 39, 46.3, 49.4, 51.5, and 64.5 with detection ranges of approximately 700 m (Hager 2016).

Ten adult Atlantic sturgeon (FL > 1550 mm) were implanted with 10-year transmitters (Vemco V16) and two others with 18-month (Vemco V13) transmitters at rkm 129.5 between 19 August and 25 September, 2013. To ensure there were no behavioral effects from surgical transmitter implantation, we use the following year's spawning behavior to demonstrate the SIRI model. In the fall of 2014, nine of these individuals returned to spawn, but one of the 18-month transmitters failed after 15 months, so only eight transmitters were used for this SIRI demonstration. The removed transmitter was last detected at rkm 14 on 21 October 2014 but because the transmitter's battery was failing, the individual was only detected 8 times at 3 stations during outmigration and only 10 times the entire month of October. Atlantic sturgeon migrate from ocean water to fresh water to spawn so movements were monitored during the immigration and emigration periods from the first arrival on May 31, 2014 through the last departure on November 3, 2014. Immigration was complete on August 14, 2014 and at no time did any of the sturgeon return to the oligohaline station until emigrating. Emigration commenced September 29, 2014. Therefore, the immigration period lasted for 76 days and the emigration period lasted for 36 days.

As validation of the percent SIRI estimates for each station, we present a kernel density estimate analysis (Rosenblatt 1956, Whittle 1958) of the same dataset, estimating the habitat use during immigration and emigration. Kernel density estimates were calculated within ArcGIS pro 2.9.3 (Esri Inc.). Kernel density probabilities calculated the diminished density radii around the passive receivers (Silverman 1986), effectively revealing the areas of the York River most heavily used during immigration and emigration. We report the results of percent SIRI and kernel density estimates during the immigration and emigration periods for comparative purposes.

Results

The SIRI effectively combines count data, total detections, and days present during a migratory period into one index that provides a standard value for each passive telemetry station (Table 2). During immigration, half of the fish avoided detection at rkm 14 and 26.8, while all fish were detected at all other stations. Nearly twice as many detections occurred at the station with highest salinity located at rkm 11.3 than any other station (Table 2). However, numbers of detections and frequency of occurrence were slightly higher at rkm 64.5, the station with lowest salinity and last location before entering freshwater. During emigration, all fish were detected at all stations with the exception of one fish at rkm 14. The highest counts, detections, and percent occupancy occurred at rkm 26.8. The SIRI objectively ranks the relative importance of all 10 stations, with stations at rkm 11.3 and 64.5 indicated as being most important during immigration and rkm 26.8

as being of primary importance during emigration. Kernel density estimations conducted using the same data used for the SIRI reveal similarly modeled habitat utilization (Figure 1).

Temporal elasticity in the SIRI equation also allowed for weekly analyses of habitat utilization during immigration and emigration (Table 3). Because immigration occurs over broader time frames, many weeks are observations of individual fish. Each week, the most frequently used immigration stations were near the mouth of the York River or near the saltwater interface. Emigration time frames were more focused and therefore in the first week, most fish were near the saltwater interface but in all subsequent weeks, all fish spent most of their time at rkm 26.8. In all cases, individual stations in different weeks showed variability, but the overall trends observed in Table 2 are still apparent.

Discussion

The percent diet SIRI is based on a long-accepted approach of deriving a single index from stomach content analyses that can be used to compare the relative importance of each prey item. The SIRI provides a single index to compare the varied types of data inherent to tracking studies to identify the relative importance of receiver sites based on detections. The major shortcomings of diet studies are a difference in digestion rate for some foods and a difference in ease of identification between food resources (Buckland et al. 2017). Further, because of the challenges with identification, food items are not always identified to the same taxonomic level (Brown et al. 2012). Similarly, the SIRI or any other passive telemetry study could be criticized for variability in transmitter detection range due to tag transmission power and/or environmental conditions affecting receiver receptive distances. While there is no overlap in receiver coverage in this study, each station is evaluated independently, so if signals from an individual fish were recorded on multiple receivers, the final product would reveal the importance of that general area. Depending on the area covered by the passive telemetry array, conditions affecting detection distance may act uniformly on all receivers in the study (Mathies et al. 2014). The SIRI relies on the assumption that habitat is selected based on its benefit to species' survival and while an animal may have to move through less optimal physiological conditions to reach preferred habitats, over sufficient time the SIRI will indicate sites of preferred occupancy. Another important assumption to the application of the SIRI is that the sample size and its biological characteristics adequately represent a non-biased subset of the population being examined. At low sample sizes, of receiver coverage or tracked individuals, one runs the risk of telemetered individuals inadequately reflecting the true habitat occupation of the species or population. Researchers have a responsibility to ensure that the overall composition of telemetered individuals is representative of the population being described. We recommend considering life stage, sex, behavior or habitat use, abiotic conditions, and whether the analysis is considering one population or several, at a minimum, to address this issue. In our SIRI all sturgeon were adult males that exhibit similar behavior during the spawning season (Hager et al. 2020) which were all genetically assigned to the York River population (Kazyak et al. 2021).

The kernel density estimation model and SIRI both show that different York River system receiver sites were preferentially occupied by adult sturgeon during immigration versus emigration in 2014. Further, the two models show strong correlation in their outputs. During immigration, adults spent the majority of their time at a deep constriction point in the river at

rkm 11.3, with additional habitat selection closer to the freshwater-saltwater interface. While fish were detected at all stations to some extent during immigration, the mainstem York River channel was used more for relatively rapid upstream passage. On emigration, there was a primary preference for rkm 26.8 in the mesohaline region and a secondary preference for habitats around rkm 11.3 near the confluence with the bay. Though these locations differ in their salinity the preference exhibited for these locations in 2014 may be linked to the fact that both were located in zones of gradual transition between salinities. Because the SIRI model relies on temporal detection information and not just raw detection data it can be easily manipulated to examine the effects of temporal alterations in attributes like salinity, temperature, or dissolved oxygen on habitat selection. Therefore, SIRI is not only able to identify and rank the relative importance of habitats but it can be more easily manipulated to examine preference for these locations under varied physical conditions. Because the kernel analysis' relies on raw data alone it is not as well suited for such temporal analytical manipulation. Further, the SIRI model can account for periods of missing receiver days if a station were lost or the battery failed during the study and account for shorter sampling time at one station relative to other stations during the study, which the kernel model does not.

Another significant advantage to application of the SIRI is that it allows for the development of models that can incorporate a single standardized value, rank, or score per monitored site. This index value is calculated by real-time occupation data along with real time abiotic data. Thus, this relatively simple index provides a means of advancing array-based analysis. Acquiring a single representative value per site, at specific times when we know individuals to be present, allows spatial and temporal comparisons within and between studies. Models that build upon the SIRI and incorporate abiotic variables provide a means of assigning habitat value based on environmental attributes, similar to habitat suitability index models, but more simply incorporate telemetry detection data (Roloff and Kernohan 1999, Mitchell et al. 2002, Yu et al. 2018). Such models can guide management to avoid sites or regions with elevated potential interaction rates between human-caused stressors and species of interest and thus minimize harm, or be used to ensure desired attributes are incorporated into habitat improvement or recovery projects. Another added advantage of the SIRI is its flexibility, in which the analysis considerations can be modified to suit the investigator's hypothesis. In this case, we used a day as our set temporal component but studies on differences in habitat use between day and night, weeks, seasons, years, or any other appropriate segmentation (e.g. temperature ranges) could be applied. Developing an index of relative importance, which we have demonstrated here, will standardize habitat occupancy studies, increasing site specific telemetry utility across geographic scales.

Acknowledgments

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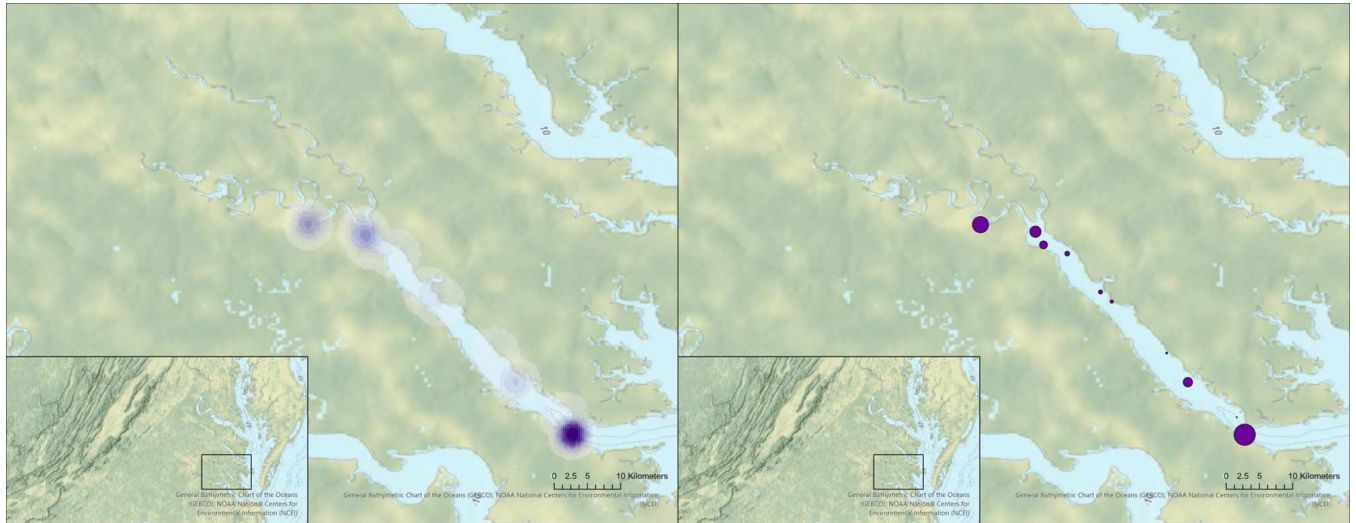
Figure 1a. Depiction of relative habitat selection during immigration during the 2014 Atlantic sturgeon spawning run using the kernel density estimator (left panel) and site-specific index of relative importance (right panel).
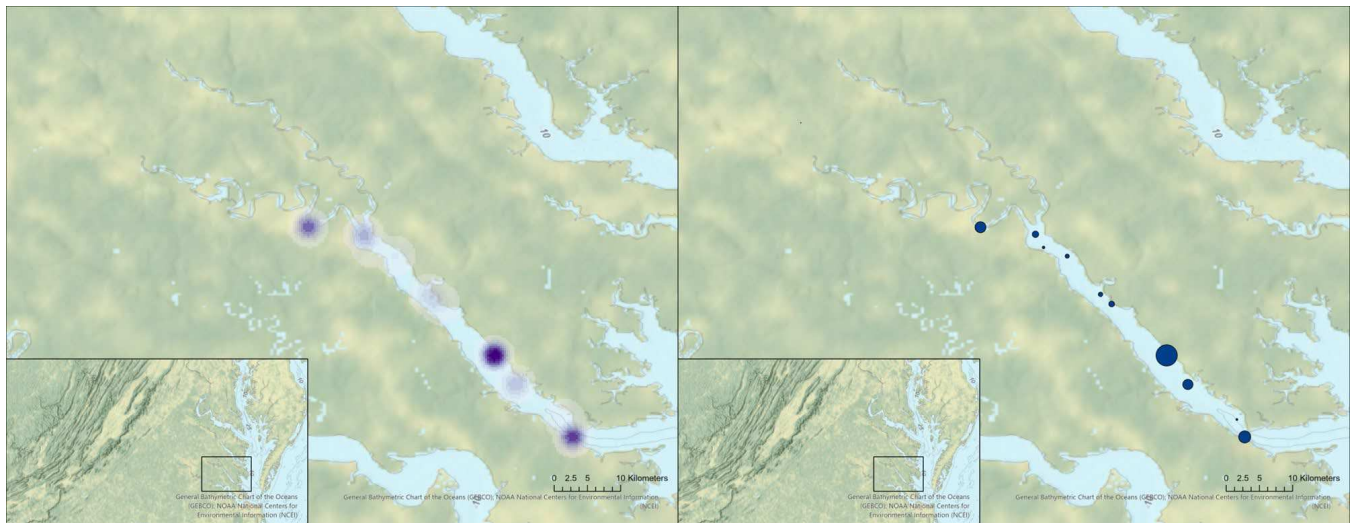
Figure 1b. Depiction of relative habitat selection during emigration during the 2014 Atlantic sturgeon spawning run using the kernel density estimator (left) and site-specific index of relative importance (right).

Table 1. Salinity variation within the York River and lower Pamunkey River during immigration and emigration periods in 2014, where rkm is river kilometer and salinity is expressed in units of parts per thousand.

Rkm	10	15	20	25	30	35	40	45	50	55	60	65	70
Salinity	18-20	16-18	14-16	12-14	9-12	7-11	3-10	2-9	2-7	1-6	1-4	1-2	0-1

Table 2. Site specific data during a) immigration and b) emigration are organized by river kilometer, count data (SN), detection data (SD), percent site-specific numbers (%SN), percent site-specific detections (%SD), frequency of occupation (%T), calculated SIRI, and % SIRI. Values for each category were rounded to the nearest hundredth except for the SIRI calculation to prevent one value from being rounded to 0.

a)

Site km	SN	Detection	%SN	%SD	%T	SIRI	%SIRI
11.3	16	1014	0.12	0.35	0.21	0.049	0.26
14	7	22	0.05	0.01	0.09	0.003	0.01
20.3	15	318	0.12	0.11	0.20	0.022	0.12
26.8	8	77	0.06	0.03	0.11	0.005	0.02
36.8	11	75	0.09	0.03	0.14	0.008	0.04
39	11	142	0.09	0.05	0.14	0.010	0.05
46.3	13	90	0.10	0.03	0.17	0.011	0.06
49.4	15	216	0.12	0.07	0.20	0.019	0.10
51.5	15	448	0.12	0.15	0.20	0.027	0.14
64.5	18	530	0.14	0.18	0.24	0.038	0.20

b)

Site km	SN	Detection	%SN	%SD	%T	SIRI	%SIRI
11.3	17	844	0.12	0.20	0.36	0.057	0.15
14	9	30	0.06	0.01	0.22	0.008	0.02
20.3	19	420	0.13	0.10	0.42	0.048	0.13
26.8	25	1094	0.17	0.26	0.47	0.101	0.27
36.8	15	169	0.10	0.04	0.36	0.026	0.07
39	12	264	0.08	0.06	0.28	0.020	0.06
46.3	12	115	0.08	0.03	0.33	0.018	0.05
49.4	9	98	0.06	0.02	0.25	0.011	0.03
51.5	12	475	0.08	0.11	0.31	0.03	0.08
64.5	16	750	0.11	0.18	0.36	0.052	0.14

Table 3. Weekly habitat use at each river kilometer (rkm), shown as % SIRI, for a) immigration and b) emigration through the saline portions of the lower Pamunkey and mainstem York rivers. Stations with no detections in a week were left blank. The last week of the immigration period was six days and emigration was eight days, all other weeks were seven days.

a)

Dates	rkm 11.3	rkm 14	rkm 20.3	rkm 26.8	rkm 36.8	rkm 39	rkm 46.3	rkm 49.4	rkm 51.5	rkm 64.5
5/31-6/6	0.29	0.08	0.29	0.13	0.03	0.03	0.02	0.04	0.05	0.04
6/7-13									0.05	0.95
6/14-20	0.52	0.48								
6/21-27	0.02	0.01	0.22	0.08	0.06	0.07	0.05	0.16	0.18	0.15
6/28-7/4	0.02		0.10	0.05	0.08	0.12	0.07	0.10	0.16	0.30
7/5-11					0.11	0.30	0.12	0.19	0.15	0.13
7/12-18	0.95	0.02	0.03							
7/19-25	0.17		0.50		0.06	0.05	0.05	0.05	0.07	0.05
7/26-8/1	0.05		0.03	0.01	0.02	0.03	0.14	0.18	0.27	0.27
8/2-8/8										
8/9-8/14	0.17		0.04	0.03	0.05	0.03	0.04	0.19	0.34	0.11

b)

Dates	rkm 11.3	rkm 14	rkm 20.3	rkm 26.8	rkm 36.8	rkm 39	rkm 46.3	rkm 49.4	rkm 51.5	rkm 64.5
9/29-10/5	0.18	0.01	0.03	0.01	0.01	0.01	0.04	0.05	0.13	0.53
10/6-10/12	0.02		0.12	0.47	0.08	0.11	0.08	0.03	0.05	0.04
10/13-10/19	0.34	0.02	0.10	0.41	0.06	0.03	0.02		0.01	0.01
10/20-10/26	0.22	0.14	0.18	0.32	0.01	0.01	0.01	0.01	0.05	0.05
10/27-11/3		0.05	0.26		0.35	0.04	0.04	0.04	0.17	0.05

Appendix B: Minor Species Detection Data (< 20 individuals).

Species	Year	Month	Individuals	Detections	Days
Unknown	2017	01	1	1	1
Unknown	2017	02	1	1	1
Unknown	2017	07	1	1	1
Unknown	2017	11	1	14	1
Unknown	2018	01	3	57	3
Unknown	2018	02	1	128	1
Unknown	2018	11	2	9	2
Unknown	2019	02	1	14	1
Unknown	2019	03	1	163	2
Unknown	2019	06	1	120	1
Unknown	2019	07	1	21	1
Unknown	2019	09	1	1	1
Unknown	2019	10	2	79	2
Unknown	2019	11	3	64	3
Unknown	2020	01	1	56	2
Unknown	2020	02	1	1	1
Unknown	2020	03	4	66	3
Unknown	2020	04	2	9	2
Unknown	2020	05	2	99	2
Unknown	2020	06	1	28	1
American shad	2020	05	1	8	1
Atlantic angelshark	2018	05	1	349	1
Atlantic angelshark	2019	05	1	55	1
Atlantic bluefin tuna	2017	01	1	32	1
Black drum	2016	08	1	1	1
Bull shark	2017	07	1	2	1
Bull shark	2017	08	1	5	3
Common thresher shark	2019	10	2	132	2
Common thresher shark	2019	11	1	5	1
Cownose ray	2016	10	1	10	1
Cownose ray	2017	09	1	38	1
Cownose ray	2017	10	2	13	2
Cownose ray	2017	11	1	2	1
Cownose ray	2018	10	4	46	4
Cownose ray	2019	10	1	47	1
Dusky shark	2016	11	1	11	1
Dusky shark	2017	09	2	44	2
Dusky shark	2017	10	1	12	1

Species	Year	Month	Individuals	Detections	Days
Dusky shark	2018	11	3	67	1
Dusky shark	2019	10	8	214	5
Finetooth shark	2018	06	1	37	1
Finetooth shark	2018	09	1	5	1
Finetooth shark	2018	10	1	46	1
Little skate	2020	01	1	25	1
Sandbar shark	2017	05	1	44	1
Sandbar shark	2017	06	2	31	2
Sandbar shark	2019	10	2	17	2
Sandbar shark	2019	11	1	14	1
Sandbar shark	2020	05	3	47	2
Sandbar shark	2020	06	2	19	2
Sandbar shark	2018	09	1	13	1
Spiny dogfish	2017	12	2	27	2
Spiny dogfish	2018	11	1	6	1
Spotted seatrout	2016	12	1	19	1
Spotted seatrout	2017	01	1	2	1
Striped bass	2016	02	1	108	1
Striped bass	2018	03	2	5	2
Striped bass	2019	05	1	5	1
Striped bass	2020	03	1	13	1
Striped bass	2020	04	1	10	1
Tarpon	2016	09	1	11	1
Tarpon	2017	08	1	10	1
Tarpon	2018	07	2	26	3
Tarpon	2018	10	1	12	1
Tiger shark	2016	09	1	2	1
Tiger shark	2016	10	1	76	2
Winter skate	2018	03	1	2810	6

Appendix C: Taggers by Species

Species	Tagger	Tags Detected	Institute
Atlantic sturgeon	Matt Balazik	92	US Army Corps of Engineers
Atlantic sturgeon	Dewayne Fox	86	Delaware State University
Atlantic sturgeon	Eric Hilton	52	Virginia Institute of Marine Science
Atlantic sturgeon	Keith Dunton	48	Monmouth University
Atlantic sturgeon	Christian Hager	31	Chesapeake Scientific LLC

Species	Tagger	Tags Detected	Institute
Atlantic sturgeon	Bill Post	28	South Carolina Department of Natural Resources
Atlantic sturgeon	Evan Ingram	24	Stony Brook University
Atlantic sturgeon	Chuck Stence	14	Maryland Department of Natural Resources
Atlantic sturgeon	Tom Savoy	6	Connecticut Department of Energy and Environmental Protection
Atlantic sturgeon	Mike Loeffler	3	North Carolina Division of Marine Fisheries
Atlantic sturgeon	Anne Wright	3	Virginia Commonwealth University
Atlantic sturgeon	Kristine Edwards	1	New York State Thruway Authority
Atlantic sturgeon	Hal Brundage	1	Environmental Research and Consulting Inc.
Atlantic sturgeon	Doug Peterson	1	University of Georgia
Atlantic sturgeon	Ian Park	1	Delaware Division of Fish and Wildlife
Atlantic sturgeon	Jake Labelle	1	Wildlife Conservation Society
Cobia	Riley Gallagher	35	North Carolina State University
Cobia	Kevin Weng	32	Virginia Institute of Marine Science
Cobia	Steve Poland	3	North Carolina Division of Marine Fisheries
Cobia	Matt Ogburn	1	Smithsonian Institute
Cobia	Matt Perkinson	1	South Carolina Department of Natural Resources
Sand tiger shark	Jake Labelle	29	Wildlife Conservation Society
Sand tiger shark	Danielle Haulsee	16	University of Delaware
Sand tiger shark	Madeline Marens	13	University of North Carolina Wilmington
Sand tiger shark	Dewayne Fox	9	Delaware State University
Sand tiger shark	Greg Skomal	8	Massachusetts Division of Marine Fisheries
Sand tiger shark	Jeff Kneebone	8	New England Aquarium
Sand tiger shark	Keith Dunton	7	Monmouth University
Sand tiger shark	Jennifer Wyffels	2	Southeast Zoo Alliance for Reproduction and Conservation
Sand tiger shark	Bryan Frazier	1	South Carolina Department of Natural Resources
Sand tiger shark	Mike Frisk	1	Stony Brook University
Blacktip shark	Stephen Kajiura	15	Florida Atlantic University
Blacktip shark	Bryan Frazier	4	South Carolina Department of Natural Resources
Blacktip shark	Keith Dunton	2	Stony Brook University
Blacktip shark	Mike Frisk	1	Stony Brook University

Species	Tagger	Tags Detected	Institute
White shark	Greg Skomal	13	Massachusetts Division of Marine Fisheries
White shark	Tobey Curtis	6	National Oceanic and Atmospheric Administration
White shark	Bryan Franks	1	OCEARCH
Dusky shark	Matt Ogburn	5	Smithsonian Institute
Dusky shark	Charles Bangley	5	Smithsonian Institute
Dusky shark	Tobey Curtis	1	National Oceanic and Atmospheric Administration
Dusky shark	Keith Dunton	1	Stony Brook University
Sandbar shark	Keith Dunton	7	Monmouth University
Sandbar shark	Caroline Collatos	2	Coastal Carolina University
Sandbar shark	Steve Szedlmayer	1	Auburn University
Sandbar shark	Mike Frisk	1	Stony Brook University
Cownose ray	Matt Ogburn	8	Smithsonian Institute
Cownose ray	Charles Bangley	1	Smithsonian Institute
Striped bass	Ben Gahagen	4	Massachusetts Division of Marine Fisheries
Striped bass	Gail Wippelhauser	1	Maine Department of Marine Resources
Striped bass	Dave Secor	1	University of Maryland Eastern Shore
Tarpon	Andy Danylchuk	4	Bonefish and Tarpon Trust
Common thresher shark	Mike Frisk	3	Stony Brook University
Spiny dogfsih	Keith Dunton	3	Stony Brook University
Spotted seatrout	Pat Mcgrath	2	Virginia Institute of Marine Science
Atlantic angelshark	Keith Dunton	2	Stony Brook University
Tiger shark	Neil Hammerschlag	1	Rosenstiel School of Marine and Atmospheric Science
Tiger shark	Bryan Frazier	1	South Carolina Department of Natural Resources
American shad	Holly White	1	North Carolina Division of Marine Fisheries
Atlantic bluefin tuna	Barbara Block	1	Stanford University
Black drum	Eric Reyier	1	Kennedy Space Center
Bull shark	Debra Abercrombie	1	Stony Brook University
Finetooth shark	Eric Reyier	1	Kennedy Space Center
Little skate	Mike Frisk	1	Stony Brook University
Spinner shark	Matt Ogburn	1	Smithsonian Institute
Winter skate	Dewayne Fox	1	Delaware State University
?	N/A	29	N/A

Appendix D: Major Species Detection Data

D.1 Atlantic sturgeon regional detections by year and month

Species	Year	Month	Individuals	Detections	Days	Temperature (C°)
Atlantic sturgeon	2015	Dec	7	123	6	14.47
Atlantic sturgeon	2016	Jan	19	222	14	10.31
Atlantic sturgeon	2016	Feb	7	162	6	6.88
Atlantic sturgeon	2016	Mar	12	278	8	8.23
Atlantic sturgeon	2016	Apr	21	369	14	10.81
Atlantic sturgeon	2016	May	4	119	4	13.94
Atlantic sturgeon	2016	Jun	2	3	2	16.21
Atlantic sturgeon	2016	Jul	0	0	0	17.02
Atlantic sturgeon	2016	Aug	0	0	0	16.77
Atlantic sturgeon	2016	Sep	2	58	2	23.93
Atlantic sturgeon	2016	Oct	5	113	6	21.22
Atlantic sturgeon	2016	Nov	42	1339	22	16.37
Atlantic sturgeon	2016	Dec	28	500	21	11.48
Atlantic sturgeon	2017	Jan	11	390	10	8.59
Atlantic sturgeon	2017	Feb	2	222	3	8.06
Atlantic sturgeon	2017	Mar	18	257	15	8.55
Atlantic sturgeon	2017	Apr	18	385	14	10.42
Atlantic sturgeon	2017	May	8	133	6	14.34
Atlantic sturgeon	2017	Jun	3	19	3	16.77
Atlantic sturgeon	2017	Jul	0	0	0	14.13
Atlantic sturgeon	2017	Aug	0	0	0	19.93
Atlantic sturgeon	2017	Sep	0	0	0	23.71
Atlantic sturgeon	2017	Oct	6	133	5	21.79
Atlantic sturgeon	2017	Nov	47	798	24	17.03
Atlantic sturgeon	2017	Dec	34	963	23	12.73
Atlantic sturgeon	2018	Jan	4	137	3	5.58
Atlantic sturgeon	2018	Feb	10	290	10	5.69
Atlantic sturgeon	2018	Mar	15	209	13	6.39
Atlantic sturgeon	2018	Apr	30	938	23	8.55
Atlantic sturgeon	2018	May	14	282	16	11.8
Atlantic sturgeon	2018	Jun	2	23	2	16.56
Atlantic sturgeon	2018	Jul	0	0	0	20.41
Atlantic sturgeon	2018	Aug	0	0	0	18.25
Atlantic sturgeon	2018	Sep	0	0	0	22.99
Atlantic sturgeon	2018	Oct	6	68	5	22.92
Atlantic sturgeon	2018	Nov	24	308	16	16.94
Atlantic sturgeon	2018	Dec	15	176	8	11.05

Species	Year	Month	Individuals	Detections	Days	Temperature (C°)
Atlantic sturgeon	2019	Jan	6	244	4	8.72
Atlantic sturgeon	2019	Feb	8	238	9	7.43
Atlantic sturgeon	2019	Mar	18	462	15	7.58
Atlantic sturgeon	2019	Apr	27	1286	23	9.75
Atlantic sturgeon	2019	May	17	349	15	12.58
Atlantic sturgeon	2019	Jun	0	0	0	14.51
Atlantic sturgeon	2019	Jul	0	0	0	14.29
Atlantic sturgeon	2019	Aug	0	0	0	16.05
Atlantic sturgeon	2019	Sep	2	77	3	23.42
Atlantic sturgeon	2019	Oct	6	132	7	21.33
Atlantic sturgeon	2019	Nov	30	552	19	16.17
Atlantic sturgeon	2019	Dec	5	139	5	11.33
Atlantic sturgeon	2020	Jan	6	112	5	9.78
Atlantic sturgeon	2020	Feb	6	123	5	8.32
Atlantic sturgeon	2020	Mar	10	273	11	9.26
Atlantic sturgeon	2020	Apr	15	249	13	11.24
Atlantic sturgeon	2020	May	7	68	9	13.93

D.2 Atlantic sturgeon detections by receiver, month, and year

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Atlantic Sturgeon	BOEM 10	Jan	2016	3	29	3
Atlantic Sturgeon	BOEM 10	Jan	2017	4	56	5
Atlantic Sturgeon	BOEM 10	Jan	2018	2	31	2
Atlantic Sturgeon	BOEM 10	Jan	2019	4	62	3
Atlantic Sturgeon	BOEM 10	Jan	2020	2	17	2
Atlantic Sturgeon	BOEM 10	Feb	2016	2	46	2
Atlantic Sturgeon	BOEM 10	Feb	2017	2	57	3
Atlantic Sturgeon	BOEM 10	Feb	2018	4	71	4
Atlantic Sturgeon	BOEM 10	Feb	2019	3	16	3
Atlantic Sturgeon	BOEM 10	Feb	2020	3	32	3
Atlantic Sturgeon	BOEM 10	Mar	2016	7	53	6
Atlantic Sturgeon	BOEM 10	Mar	2017	7	43	7
Atlantic Sturgeon	BOEM 10	Mar	2018	3	23	3
Atlantic Sturgeon	BOEM 10	Mar	2019	5	98	6
Atlantic Sturgeon	BOEM 10	Mar	2020	5	58	8
Atlantic Sturgeon	BOEM 10	Apr	2016	10	68	8
Atlantic Sturgeon	BOEM 10	Apr	2017	8	92	7
Atlantic Sturgeon	BOEM 10	Apr	2018	17	303	15
Atlantic Sturgeon	BOEM 10	Apr	2019	15	66	12
Atlantic Sturgeon	BOEM 10	Apr	2020	7	71	6
Atlantic Sturgeon	BOEM 10	May	2016	1	5	1
Atlantic Sturgeon	BOEM 10	May	2017	2	13	2
Atlantic Sturgeon	BOEM 10	May	2018	6	32	5
Atlantic Sturgeon	BOEM 10	May	2019	5	42	5
Atlantic Sturgeon	BOEM 10	May	2020	4	20	4

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Atlantic Sturgeon	BOEM 10	Sep	2016	1	18	1
Atlantic Sturgeon	BOEM 10	Sep	2019	1	4	1
Atlantic Sturgeon	BOEM 10	Oct	2016	3	45	4
Atlantic Sturgeon	BOEM 10	Oct	2017	4	74	4
Atlantic Sturgeon	BOEM 10	Oct	2019	3	46	4
Atlantic Sturgeon	BOEM 10	Nov	2016	15	182	14
Atlantic Sturgeon	BOEM 10	Nov	2017	20	149	13
Atlantic Sturgeon	BOEM 10	Nov	2018	12	52	9
Atlantic Sturgeon	BOEM 10	Nov	2019	15	119	11
Atlantic Sturgeon	BOEM 10	Dec	2015	3	38	3
Atlantic Sturgeon	BOEM 10	Dec	2016	13	79	13
Atlantic Sturgeon	BOEM 10	Dec	2017	14	124	11
Atlantic Sturgeon	BOEM 10	Dec	2018	7	45	6
Atlantic Sturgeon	BOEM 10	Dec	2019	2	50	2
Atlantic Sturgeon	BOEM 11	Jan	2016	11	78	8
Atlantic Sturgeon	BOEM 11	Jan	2017	1	6	1
Atlantic Sturgeon	BOEM 11	Jan	2018	1	6	1
Atlantic Sturgeon	BOEM 11	Jan	2019	2	18	2
Atlantic Sturgeon	BOEM 11	Jan	2020	3	10	2
Atlantic Sturgeon	BOEM 11	Feb	2016	2	7	2
Atlantic Sturgeon	BOEM 11	Feb	2017	1	13	1
Atlantic Sturgeon	BOEM 11	Feb	2018	3	13	3
Atlantic Sturgeon	BOEM 11	Feb	2019	6	100	7
Atlantic Sturgeon	BOEM 11	Mar	2016	7	100	6
Atlantic Sturgeon	BOEM 11	Mar	2017	4	46	5
Atlantic Sturgeon	BOEM 11	Mar	2018	7	56	8
Atlantic Sturgeon	BOEM 11	Mar	2019	8	97	7
Atlantic Sturgeon	BOEM 11	Mar	2020	3	57	4
Atlantic Sturgeon	BOEM 11	Apr	2016	9	99	7
Atlantic Sturgeon	BOEM 11	Apr	2017	8	67	8
Atlantic Sturgeon	BOEM 11	Apr	2018	17	159	16
Atlantic Sturgeon	BOEM 11	Apr	2019	7	19	7
Atlantic Sturgeon	BOEM 11	Apr	2020	7	50	6
Atlantic Sturgeon	BOEM 11	May	2016	3	71	3
Atlantic Sturgeon	BOEM 11	May	2017	5	43	4
Atlantic Sturgeon	BOEM 11	May	2018	6	55	6
Atlantic Sturgeon	BOEM 11	May	2019	7	43	7
Atlantic Sturgeon	BOEM 11	May	2020	1	7	1
Atlantic Sturgeon	BOEM 11	Jun	2017	1	6	1
Atlantic Sturgeon	BOEM 11	Jun	2018	2	12	2
Atlantic Sturgeon	BOEM 11	Sep	2016	1	18	1
Atlantic Sturgeon	BOEM 11	Oct	2016	2	30	2
Atlantic Sturgeon	BOEM 11	Oct	2017	3	30	2
Atlantic Sturgeon	BOEM 11	Oct	2018	1	5	1
Atlantic Sturgeon	BOEM 11	Oct	2019	5	55	6
Atlantic Sturgeon	BOEM 11	Nov	2016	18	190	16
Atlantic Sturgeon	BOEM 11	Nov	2017	17	178	14
Atlantic Sturgeon	BOEM 11	Nov	2018	12	135	9
Atlantic Sturgeon	BOEM 11	Nov	2019	19	172	14
Atlantic Sturgeon	BOEM 11	Dec	2015	3	17	2

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Atlantic Sturgeon	BOEM 11	Dec	2016	13	96	12
Atlantic Sturgeon	BOEM 11	Dec	2017	19	204	13
Atlantic Sturgeon	BOEM 11	Dec	2018	6	37	4
Atlantic Sturgeon	BOEM 11	Dec	2019	1	3	1
Atlantic Sturgeon	BOEM 12	Jan	2016	3	30	3
Atlantic Sturgeon	BOEM 12	Jan	2017	1	1	1
Atlantic Sturgeon	BOEM 12	Jan	2018	2	35	2
Atlantic Sturgeon	BOEM 12	Jan	2020	2	39	2
Atlantic Sturgeon	BOEM 12	Feb	2018	3	31	3
Atlantic Sturgeon	BOEM 12	Feb	2019	3	51	4
Atlantic Sturgeon	BOEM 12	Feb	2020	1	9	1
Atlantic Sturgeon	BOEM 12	Mar	2016	6	41	4
Atlantic Sturgeon	BOEM 12	Mar	2017	4	16	5
Atlantic Sturgeon	BOEM 12	Mar	2018	7	37	6
Atlantic Sturgeon	BOEM 12	Mar	2019	10	64	9
Atlantic Sturgeon	BOEM 12	Mar	2020	6	74	5
Atlantic Sturgeon	BOEM 12	Apr	2016	5	32	5
Atlantic Sturgeon	BOEM 12	Apr	2017	4	17	4
Atlantic Sturgeon	BOEM 12	Apr	2018	13	63	12
Atlantic Sturgeon	BOEM 12	Apr	2019	4	22	4
Atlantic Sturgeon	BOEM 12	Apr	2020	3	40	3
Atlantic Sturgeon	BOEM 12	May	2016	2	4	2
Atlantic Sturgeon	BOEM 12	May	2017	3	19	3
Atlantic Sturgeon	BOEM 12	May	2018	5	29	5
Atlantic Sturgeon	BOEM 12	May	2019	5	26	5
Atlantic Sturgeon	BOEM 12	May	2020	2	3	2
Atlantic Sturgeon	BOEM 12	Jun	2017	2	2	1
Atlantic Sturgeon	BOEM 12	Jun	2018	2	11	2
Atlantic Sturgeon	BOEM 12	Sep	2019	1	69	2
Atlantic Sturgeon	BOEM 12	Oct	2016	3	10	4
Atlantic Sturgeon	BOEM 12	Oct	2018	1	5	1
Atlantic Sturgeon	BOEM 12	Oct	2019	2	6	2
Atlantic Sturgeon	BOEM 12	Nov	2016	17	86	13
Atlantic Sturgeon	BOEM 12	Nov	2017	12	34	9
Atlantic Sturgeon	BOEM 12	Nov	2018	7	22	7
Atlantic Sturgeon	BOEM 12	Nov	2019	15	152	11
Atlantic Sturgeon	BOEM 12	Dec	2015	3	13	2
Atlantic Sturgeon	BOEM 12	Dec	2016	8	58	7
Atlantic Sturgeon	BOEM 12	Dec	2017	16	136	13
Atlantic Sturgeon	BOEM 12	Dec	2018	2	13	2
Atlantic Sturgeon	BOEM 12	Dec	2019	2	25	3
Atlantic Sturgeon	BOEM 7	Jan	2016	3	25	3
Atlantic Sturgeon	BOEM 7	Jan	2017	7	226	8
Atlantic Sturgeon	BOEM 7	Feb	2016	2	37	2
Atlantic Sturgeon	BOEM 7	Feb	2017	2	36	3
Atlantic Sturgeon	BOEM 7	Feb	2018	6	74	6
Atlantic Sturgeon	BOEM 7	Mar	2016	2	9	2
Atlantic Sturgeon	BOEM 7	Mar	2017	9	68	9
Atlantic Sturgeon	BOEM 7	Mar	2018	6	40	6
Atlantic Sturgeon	BOEM 7	Mar	2019	7	87	8

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Atlantic Sturgeon	BOEM 7	Apr	2016	10	60	8
Atlantic Sturgeon	BOEM 7	Apr	2017	4	20	4
Atlantic Sturgeon	BOEM 7	Apr	2018	12	146	12
Atlantic Sturgeon	BOEM 7	Apr	2019	14	968	17
Atlantic Sturgeon	BOEM 7	Apr	2020	1	12	1
Atlantic Sturgeon	BOEM 7	May	2016	1	9	1
Atlantic Sturgeon	BOEM 7	May	2017	2	9	1
Atlantic Sturgeon	BOEM 7	May	2018	7	114	12
Atlantic Sturgeon	BOEM 7	May	2019	8	138	8
Atlantic Sturgeon	BOEM 7	May	2020	3	21	4
Atlantic Sturgeon	BOEM 7	Jun	2016	2	3	2
Atlantic Sturgeon	BOEM 7	Jun	2017	2	11	2
Atlantic Sturgeon	BOEM 7	Sep	2016	1	2	1
Atlantic Sturgeon	BOEM 7	Oct	2016	2	12	2
Atlantic Sturgeon	BOEM 7	Oct	2017	2	12	2
Atlantic Sturgeon	BOEM 7	Oct	2018	2	5	2
Atlantic Sturgeon	BOEM 7	Oct	2019	2	14	2
Atlantic Sturgeon	BOEM 7	Nov	2016	17	128	13
Atlantic Sturgeon	BOEM 7	Nov	2017	16	198	14
Atlantic Sturgeon	BOEM 7	Nov	2018	4	21	4
Atlantic Sturgeon	BOEM 7	Dec	2015	1	1	1
Atlantic Sturgeon	BOEM 7	Dec	2016	3	19	3
Atlantic Sturgeon	BOEM 7	Dec	2017	13	195	11
Atlantic Sturgeon	BOEM 7	Dec	2018	4	25	2
Atlantic Sturgeon	BOEM 8	Jan	2016	4	22	3
Atlantic Sturgeon	BOEM 8	Jan	2017	5	50	3
Atlantic Sturgeon	BOEM 8	Jan	2018	1	28	1
Atlantic Sturgeon	BOEM 8	Jan	2019	4	100	4
Atlantic Sturgeon	BOEM 8	Jan	2020	3	19	3
Atlantic Sturgeon	BOEM 8	Feb	2016	2	18	2
Atlantic Sturgeon	BOEM 8	Feb	2017	1	37	2
Atlantic Sturgeon	BOEM 8	Feb	2018	5	73	4
Atlantic Sturgeon	BOEM 8	Feb	2019	5	33	5
Atlantic Sturgeon	BOEM 8	Feb	2020	3	33	3
Atlantic Sturgeon	BOEM 8	Mar	2016	3	20	2
Atlantic Sturgeon	BOEM 8	Mar	2017	7	41	5
Atlantic Sturgeon	BOEM 8	Mar	2018	6	22	6
Atlantic Sturgeon	BOEM 8	Mar	2019	5	67	5
Atlantic Sturgeon	BOEM 8	Mar	2020	5	42	5
Atlantic Sturgeon	BOEM 8	Apr	2016	5	33	5
Atlantic Sturgeon	BOEM 8	Apr	2017	9	95	9
Atlantic Sturgeon	BOEM 8	Apr	2018	12	79	11
Atlantic Sturgeon	BOEM 8	Apr	2019	14	145	13
Atlantic Sturgeon	BOEM 8	Apr	2020	6	29	6
Atlantic Sturgeon	BOEM 8	May	2016	1	6	1
Atlantic Sturgeon	BOEM 8	May	2017	3	24	3
Atlantic Sturgeon	BOEM 8	May	2018	4	22	8
Atlantic Sturgeon	BOEM 8	May	2019	5	38	5
Atlantic Sturgeon	BOEM 8	May	2020	4	17	4
Atlantic Sturgeon	BOEM 8	Oct	2017	2	4	2

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Atlantic Sturgeon	BOEM 8	Oct	2019	1	6	1
Atlantic Sturgeon	BOEM 8	Nov	2016	13	169	12
Atlantic Sturgeon	BOEM 8	Nov	2017	14	83	13
Atlantic Sturgeon	BOEM 8	Nov	2019	4	48	4
Atlantic Sturgeon	BOEM 8	Dec	2015	3	17	2
Atlantic Sturgeon	BOEM 8	Dec	2016	7	49	8
Atlantic Sturgeon	BOEM 8	Dec	2017	12	154	10
Atlantic Sturgeon	BOEM 8	Dec	2019	2	36	2
Atlantic Sturgeon	BOEM 9	Jan	2016	3	38	3
Atlantic Sturgeon	BOEM 9	Jan	2017	6	51	4
Atlantic Sturgeon	BOEM 9	Jan	2018	2	37	2
Atlantic Sturgeon	BOEM 9	Jan	2019	3	64	3
Atlantic Sturgeon	BOEM 9	Jan	2020	3	27	3
Atlantic Sturgeon	BOEM 9	Feb	2016	4	54	4
Atlantic Sturgeon	BOEM 9	Feb	2017	2	79	3
Atlantic Sturgeon	BOEM 9	Feb	2018	4	28	3
Atlantic Sturgeon	BOEM 9	Feb	2019	3	38	3
Atlantic Sturgeon	BOEM 9	Feb	2020	3	49	3
Atlantic Sturgeon	BOEM 9	Mar	2016	4	55	3
Atlantic Sturgeon	BOEM 9	Mar	2017	7	43	6
Atlantic Sturgeon	BOEM 9	Mar	2018	5	31	5
Atlantic Sturgeon	BOEM 9	Mar	2019	5	49	4
Atlantic Sturgeon	BOEM 9	Mar	2020	2	42	3
Atlantic Sturgeon	BOEM 9	Apr	2016	10	77	8
Atlantic Sturgeon	BOEM 9	Apr	2017	9	94	9
Atlantic Sturgeon	BOEM 9	Apr	2018	19	188	12
Atlantic Sturgeon	BOEM 9	Apr	2019	11	66	9
Atlantic Sturgeon	BOEM 9	Apr	2020	5	47	5
Atlantic Sturgeon	BOEM 9	May	2016	2	24	2
Atlantic Sturgeon	BOEM 9	May	2017	4	25	4
Atlantic Sturgeon	BOEM 9	May	2018	6	30	7
Atlantic Sturgeon	BOEM 9	May	2019	6	62	6
Atlantic Sturgeon	BOEM 9	Sep	2016	1	20	1
Atlantic Sturgeon	BOEM 9	Sep	2019	1	4	1
Atlantic Sturgeon	BOEM 9	Oct	2016	4	16	4
Atlantic Sturgeon	BOEM 9	Oct	2017	3	13	3
Atlantic Sturgeon	BOEM 9	Oct	2018	2	53	2
Atlantic Sturgeon	BOEM 9	Oct	2019	1	5	1
Atlantic Sturgeon	BOEM 9	Nov	2016	18	584	17
Atlantic Sturgeon	BOEM 9	Nov	2017	20	156	14
Atlantic Sturgeon	BOEM 9	Nov	2018	11	78	9
Atlantic Sturgeon	BOEM 9	Nov	2019	9	61	7
Atlantic Sturgeon	BOEM 9	Dec	2015	3	37	2
Atlantic Sturgeon	BOEM 9	Dec	2016	11	199	11
Atlantic Sturgeon	BOEM 9	Dec	2017	16	150	14
Atlantic Sturgeon	BOEM 9	Dec	2018	6	56	5
Atlantic Sturgeon	BOEM 9	Dec	2019	2	25	2
Sum	all	all	All	1276	11228	981

D.3 Sand tiger shark regional detections by year and month

Species	Year	Month	Individuals	Detections	Days
Sand tiger shark	2016	05	1	17	1
Sand tiger shark	2016	07	1	23	1
Sand tiger shark	2016	08	1	6	1
Sand tiger shark	2016	10	10	277	9
Sand tiger shark	2016	11	1	36	1
Sand tiger shark	2017	04	1	21	1
Sand tiger shark	2017	05	12	167	11
Sand tiger shark	2017	06	3	170	2
Sand tiger shark	2017	09	1	14	1
Sand tiger shark	2017	10	4	28	4
Sand tiger shark	2017	11	9	119	9
Sand tiger shark	2018	04	1	5	1
Sand tiger shark	2018	05	10	130	6
Sand tiger shark	2018	06	8	205	8
Sand tiger shark	2018	07	2	36	2
Sand tiger shark	2018	08	1	316	2
Sand tiger shark	2018	09	2	943	4
Sand tiger shark	2018	10	14	466	9
Sand tiger shark	2018	11	5	157	4
Sand tiger shark	2019	05	10	119	10
Sand tiger shark	2019	06	5	80	4
Sand tiger shark	2019	10	10	201	9
Sand tiger shark	2019	11	4	517	4
Sand tiger shark	2020	04	2	114	2
Sand tiger shark	2020	05	11	224	11
Sand tiger shark	2020	06	2	70	1

D.4 Sand tiger shark detections by receiver site, month, and year

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Sand tiger shark	BOEM 10	Apr	2020	2	48	2
Sand tiger shark	BOEM 10	May	2017	6	21	5
Sand tiger shark	BOEM 10	May	2018	3	20	4
Sand tiger shark	BOEM 10	May	2019	2	22	2
Sand tiger shark	BOEM 10	May	2020	8	57	8
Sand tiger shark	BOEM 10	Jun	2017	1	23	1
Sand tiger shark	BOEM 10	Jun	2018	3	37	2
Sand tiger shark	BOEM 10	Jun	2019	1	9	1
Sand tiger shark	BOEM 10	Jun	2020	2	23	1

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Sand tiger shark	BOEM 10	Jul	2016	1	4	1
Sand tiger shark	BOEM 10	Aug	2018	1	149	1
Sand tiger shark	BOEM 10	Sep	2018	2	370	3
Sand tiger shark	BOEM 10	Oct	2016	5	44	5
Sand tiger shark	BOEM 10	Oct	2018	7	61	8
Sand tiger shark	BOEM 10	Oct	2019	5	46	5
Sand tiger shark	BOEM 10	Nov	2017	2	28	3
Sand tiger shark	BOEM 10	Nov	2018	3	54	3
Sand tiger shark	BOEM 10	Nov	2019	4	152	4
Sand tiger shark	BOEM 11	Apr	2020	1	19	1
Sand tiger shark	BOEM 11	May	2017	4	12	4
Sand tiger shark	BOEM 11	May	2018	3	22	3
Sand tiger shark	BOEM 11	May	2019	3	14	3
Sand tiger shark	BOEM 11	May	2020	5	43	6
Sand tiger shark	BOEM 11	Jun	2017	2	13	2
Sand tiger shark	BOEM 11	Jun	2018	6	56	5
Sand tiger shark	BOEM 11	Jun	2020	1	6	1
Sand tiger shark	BOEM 11	Aug	2018	1	63	1
Sand tiger shark	BOEM 11	Sep	2017	1	14	1
Sand tiger shark	BOEM 11	Sep	2018	2	226	2
Sand tiger shark	BOEM 11	Oct	2016	6	53	6
Sand tiger shark	BOEM 11	Oct	2018	7	304	7
Sand tiger shark	BOEM 11	Oct	2019	3	31	4
Sand tiger shark	BOEM 11	Nov	2016	1	21	1
Sand tiger shark	BOEM 11	Nov	2017	2	17	2
Sand tiger shark	BOEM 11	Nov	2018	1	56	1
Sand tiger shark	BOEM 11	Nov	2019	3	189	3
Sand tiger shark	BOEM 12	Apr	2020	1	6	1
Sand tiger shark	BOEM 12	May	2018	3	25	3
Sand tiger shark	BOEM 12	May	2019	3	14	3
Sand tiger shark	BOEM 12	May	2020	4	29	4
Sand tiger shark	BOEM 12	Jun	2018	4	27	3
Sand tiger shark	BOEM 12	Jun	2019	1	1	1
Sand tiger shark	BOEM 12	Jun	2020	1	4	1
Sand tiger shark	BOEM 12	Aug	2016	1	6	1
Sand tiger shark	BOEM 12	Sep	2018	1	1	1
Sand tiger shark	BOEM 12	Oct	2016	5	142	4
Sand tiger shark	BOEM 12	Oct	2018	4	20	4
Sand tiger shark	BOEM 12	Oct	2019	5	48	6
Sand tiger shark	BOEM 12	Nov	2016	1	14	1

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Sand tiger shark	BOEM 12	Nov	2017	4	19	5
Sand tiger shark	BOEM 12	Nov	2018	3	14	3
Sand tiger shark	BOEM 12	Nov	2019	2	6	2
Sand tiger shark	BOEM 7	Apr	2017	1	11	1
Sand tiger shark	BOEM 7	Apr	2018	1	5	1
Sand tiger shark	BOEM 7	May	2016	1	17	1
Sand tiger shark	BOEM 7	May	2017	4	69	4
Sand tiger shark	BOEM 7	May	2018	4	21	4
Sand tiger shark	BOEM 7	May	2019	5	16	5
Sand tiger shark	BOEM 7	May	2020	7	45	7
Sand tiger shark	BOEM 7	Jun	2017	2	21	2
Sand tiger shark	BOEM 7	Jun	2018	6	34	5
Sand tiger shark	BOEM 7	Jun	2019	4	36	4
Sand tiger shark	BOEM 7	Jun	2020	1	17	1
Sand tiger shark	BOEM 7	Jul	2016	1	19	1
Sand tiger shark	BOEM 7	Jul	2018	2	30	2
Sand tiger shark	BOEM 7	Aug	2018	1	17	1
Sand tiger shark	BOEM 7	Sep	2018	1	4	1
Sand tiger shark	BOEM 7	Oct	2016	4	21	3
Sand tiger shark	BOEM 7	Oct	2017	3	21	3
Sand tiger shark	BOEM 7	Oct	2018	3	26	3
Sand tiger shark	BOEM 7	Oct	2019	3	15	3
Sand tiger shark	BOEM 7	Nov	2017	4	22	3
Sand tiger shark	BOEM 7	Nov	2018	1	1	1
Sand tiger shark	BOEM 7	Nov	2019	1	5	1
Sand tiger shark	BOEM 8	Apr	2017	1	10	1
Sand tiger shark	BOEM 8	Apr	2020	1	20	1
Sand tiger shark	BOEM 8	May	2017	4	29	4
Sand tiger shark	BOEM 8	May	2018	4	22	3
Sand tiger shark	BOEM 8	May	2019	3	24	3
Sand tiger shark	BOEM 8	May	2020	6	50	5
Sand tiger shark	BOEM 8	Jun	2017	2	45	2
Sand tiger shark	BOEM 8	Jun	2018	4	33	3
Sand tiger shark	BOEM 8	Jun	2019	3	29	3
Sand tiger shark	BOEM 8	Jun	2020	2	20	1
Sand tiger shark	BOEM 8	Jul	2018	1	3	1
Sand tiger shark	BOEM 8	Aug	2018	1	38	1
Sand tiger shark	BOEM 8	Sep	2018	1	7	1
Sand tiger shark	BOEM 8	Oct	2017	3	5	3
Sand tiger shark	BOEM 8	Oct	2019	4	10	4

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Sand tiger shark	BOEM 8	Nov	2017	2	6	2
Sand tiger shark	BOEM 8	Nov	2019	4	17	4
Sand tiger shark	BOEM 9	Apr	2020	1	21	1
Sand tiger shark	BOEM 9	May	2017	4	36	4
Sand tiger shark	BOEM 9	May	2018	4	20	3
Sand tiger shark	BOEM 9	May	2019	3	29	3
Sand tiger shark	BOEM 9	Jun	2017	2	68	2
Sand tiger shark	BOEM 9	Jun	2018	4	18	3
Sand tiger shark	BOEM 9	Jun	2019	1	5	1
Sand tiger shark	BOEM 9	Jul	2018	1	3	1
Sand tiger shark	BOEM 9	Aug	2018	1	49	1
Sand tiger shark	BOEM 9	Sep	2018	2	335	3
Sand tiger shark	BOEM 9	Oct	2016	3	17	3
Sand tiger shark	BOEM 9	Oct	2017	1	2	1
Sand tiger shark	BOEM 9	Oct	2018	7	55	5
Sand tiger shark	BOEM 9	Oct	2019	6	51	5
Sand tiger shark	BOEM 9	Nov	2016	1	1	1
Sand tiger shark	BOEM 9	Nov	2017	2	27	3
Sand tiger shark	BOEM 9	Nov	2018	2	32	2
Sand tiger shark	BOEM 9	Nov	2019	3	148	3
Sum	all	all	all	307	4461	299

D.5 Cobia detections by year and month

Species	Year	Month	Individuals	Detections	Days
Cobia	2017	08	2	13	2
Cobia	2017	10	2	423	11
Cobia	2018	06	3	157	3
Cobia	2018	07	2	41	4
Cobia	2018	08	4	301	9
Cobia	2018	09	12	460	12
Cobia	2018	10	18	526	11
Cobia	2019	05	8	96	7
Cobia	2019	06	12	329	10
Cobia	2019	07	7	158	12
Cobia	2019	08	8	472	14
Cobia	2019	09	27	1299	13
Cobia	2019	10	24	1018	14
Cobia	2020	05	3	58	2

D.6 Cobia detections by receiver site, month, and year.

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Cobia	BOEM 10	May	2019	4	25	4
Cobia	BOEM 10	May	2020	3	29	2
Cobia	BOEM 10	Jun	2018	1	23	1
Cobia	BOEM 10	Jun	2019	4	33	4
Cobia	BOEM 10	Jul	2018	2	9	2
Cobia	BOEM 10	Jul	2019	4	45	6
Cobia	BOEM 10	Aug	2017	1	3	1
Cobia	BOEM 10	Aug	2018	3	103	4
Cobia	BOEM 10	Aug	2019	6	112	8
Cobia	BOEM 10	Sep	2018	4	172	6
Cobia	BOEM 10	Sep	2019	14	334	10
Cobia	BOEM 10	Oct	2017	1	101	4
Cobia	BOEM 10	Oct	2018	8	103	8
Cobia	BOEM 10	Oct	2019	13	279	9
Cobia	BOEM 11	May	2019	2	25	2
Cobia	BOEM 11	May	2020	2	15	1
Cobia	BOEM 11	Jun	2018	2	36	2
Cobia	BOEM 11	Jun	2019	5	44	5
Cobia	BOEM 11	Jul	2018	2	7	2
Cobia	BOEM 11	Jul	2019	1	2	1
Cobia	BOEM 11	Aug	2017	1	1	1
Cobia	BOEM 11	Aug	2018	3	37	4
Cobia	BOEM 11	Aug	2019	4	50	5
Cobia	BOEM 11	Sep	2018	6	60	5
Cobia	BOEM 11	Sep	2019	13	149	10
Cobia	BOEM 11	Oct	2017	1	89	5
Cobia	BOEM 11	Oct	2018	8	131	6
Cobia	BOEM 11	Oct	2019	12	173	9
Cobia	BOEM 12	May	2019	3	18	3
Cobia	BOEM 12	May	2020	1	13	1
Cobia	BOEM 12	Jun	2018	2	33	2
Cobia	BOEM 12	Jun	2019	6	48	5
Cobia	BOEM 12	Jul	2018	2	9	3
Cobia	BOEM 12	Jul	2019	5	45	6
Cobia	BOEM 12	Aug	2017	1	2	1
Cobia	BOEM 12	Aug	2018	2	27	3
Cobia	BOEM 12	Aug	2019	1	39	2
Cobia	BOEM 12	Sep	2018	2	8	2
Cobia	BOEM 12	Sep	2019	14	257	7

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Cobia	BOEM 12	Oct	2017	2	83	5
Cobia	BOEM 12	Oct	2018	8	43	4
Cobia	BOEM 12	Oct	2019	17	186	11
Cobia	BOEM 7	May	2019	2	9	2
Cobia	BOEM 7	Jun	2018	1	3	1
Cobia	BOEM 7	Jun	2019	8	52	6
Cobia	BOEM 7	Jul	2019	4	35	5
Cobia	BOEM 7	Aug	2018	3	53	4
Cobia	BOEM 7	Aug	2019	4	97	6
Cobia	BOEM 7	Sep	2018	7	125	7
Cobia	BOEM 7	Sep	2019	15	208	12
Cobia	BOEM 7	Oct	2017	2	24	3
Cobia	BOEM 7	Oct	2018	7	82	9
Cobia	BOEM 7	Oct	2019	11	98	10
Cobia	BOEM 8	May	2019	1	7	1
Cobia	BOEM 8	May	2020	1	1	1
Cobia	BOEM 8	Jun	2018	2	16	2
Cobia	BOEM 8	Jun	2019	8	78	8
Cobia	BOEM 8	Jul	2018	2	8	2
Cobia	BOEM 8	Jul	2019	3	13	3
Cobia	BOEM 8	Aug	2017	1	1	1
Cobia	BOEM 8	Aug	2018	2	30	4
Cobia	BOEM 8	Aug	2019	7	74	9
Cobia	BOEM 8	Sep	2018	3	26	4
Cobia	BOEM 8	Sep	2019	11	109	9
Cobia	BOEM 8	Oct	2017	2	19	3
Cobia	BOEM 8	Oct	2018	6	53	5
Cobia	BOEM 8	Oct	2019	8	49	7
Cobia	BOEM 9	May	2019	1	12	1
Cobia	BOEM 9	Jun	2018	2	46	2
Cobia	BOEM 9	Jun	2019	7	74	7
Cobia	BOEM 9	Jul	2018	2	8	2
Cobia	BOEM 9	Jul	2019	4	18	4
Cobia	BOEM 9	Aug	2017	1	6	1
Cobia	BOEM 9	Aug	2018	2	51	3
Cobia	BOEM 9	Aug	2019	4	100	6
Cobia	BOEM 9	Sep	2018	5	69	6
Cobia	BOEM 9	Sep	2019	13	242	10
Cobia	BOEM 9	Oct	2017	2	107	6
Cobia	BOEM 9	Oct	2018	9	114	7

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Cobia	BOEM 9	Oct	2019	11	233	9
Sum	all	all	all	380	5351	370

D.7 Blacktip shark regional detections by year and month

Species	Year	Month	Individuals	Detections	Days
Blacktip shark	2016	07	1	19	1
Blacktip shark	2016	08	1	14	1
Blacktip shark	2017	08	1	17	1
Blacktip shark	2017	09	1	54	1
Blacktip shark	2017	10	5	161	5
Blacktip shark	2018	06	3	37	4
Blacktip shark	2018	07	1	29	1
Blacktip shark	2018	08	2	160	3
Blacktip shark	2018	09	2	32	3
Blacktip shark	2018	10	3	652	4
Blacktip shark	2019	06	4	178	8
Blacktip shark	2019	07	3	59	4
Blacktip shark	2019	08	1	8	1
Blacktip shark	2019	09	3	106	3
Blacktip shark	2019	10	5	162	4

D.8 Blacktip shark detections by receiver site, month, and year

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Blacktip shark	BOEM 10	Jun	2019	1	18	1
Blacktip shark	BOEM 10	Jul	2016	1	8	1
Blacktip shark	BOEM 10	Jul	2018	1	11	1
Blacktip shark	BOEM 10	Jul	2019	2	26	2
Blacktip shark	BOEM 10	Aug	2016	1	1	1
Blacktip shark	BOEM 10	Aug	2018	1	26	2
Blacktip shark	BOEM 10	Sep	2017	1	4	1
Blacktip shark	BOEM 10	Sep	2018	1	27	1
Blacktip shark	BOEM 10	Sep	2019	3	28	3
Blacktip shark	BOEM 10	Oct	2017	1	21	1
Blacktip shark	BOEM 10	Oct	2018	2	326	3
Blacktip shark	BOEM 10	Oct	2019	2	7	2
Blacktip shark	BOEM 11	Jun	2018	2	12	2
Blacktip shark	BOEM 11	Jun	2019	4	44	4
Blacktip shark	BOEM 11	Jul	2016	1	6	1
Blacktip shark	BOEM 11	Jul	2018	1	1	1

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Blacktip shark	BOEM 11	Jul	2019	1	7	1
Blacktip shark	BOEM 11	Aug	2017	1	11	1
Blacktip shark	BOEM 11	Aug	2019	1	1	1
Blacktip shark	BOEM 11	Sep	2017	1	10	1
Blacktip shark	BOEM 11	Sep	2018	1	3	1
Blacktip shark	BOEM 11	Oct	2017	3	43	3
Blacktip shark	BOEM 11	Oct	2018	3	87	4
Blacktip shark	BOEM 11	Oct	2019	3	35	3
Blacktip shark	BOEM 12	Jun	2018	1	22	2
Blacktip shark	BOEM 12	Jun	2019	4	50	5
Blacktip shark	BOEM 12	Jul	2016	1	1	1
Blacktip shark	BOEM 12	Jul	2019	2	16	3
Blacktip shark	BOEM 12	Aug	2017	1	6	1
Blacktip shark	BOEM 12	Aug	2018	1	10	1
Blacktip shark	BOEM 12	Aug	2019	1	7	1
Blacktip shark	BOEM 12	Sep	2018	1	2	1
Blacktip shark	BOEM 12	Sep	2019	1	2	1
Blacktip shark	BOEM 12	Oct	2017	3	29	3
Blacktip shark	BOEM 12	Oct	2018	2	19	2
Blacktip shark	BOEM 12	Oct	2019	1	16	1
Blacktip shark	BOEM 7	Jun	2018	1	3	1
Blacktip shark	BOEM 7	Jun	2019	1	20	2
Blacktip shark	BOEM 7	Aug	2018	2	63	2
Blacktip shark	BOEM 7	Sep	2019	2	30	2
Blacktip shark	BOEM 7	Oct	2018	1	1	1
Blacktip shark	BOEM 7	Oct	2019	3	55	2
Blacktip shark	BOEM 8	Jun	2019	2	28	3
Blacktip shark	BOEM 8	Jul	2018	1	3	1
Blacktip shark	BOEM 8	Jul	2019	1	4	1
Blacktip shark	BOEM 8	Aug	2016	1	5	1
Blacktip shark	BOEM 8	Aug	2018	1	10	1
Blacktip shark	BOEM 8	Sep	2017	1	3	1
Blacktip shark	BOEM 8	Sep	2019	2	15	2
Blacktip shark	BOEM 8	Oct	2017	3	32	3
Blacktip shark	BOEM 8	Oct	2018	1	3	1
Blacktip shark	BOEM 8	Oct	2019	2	3	2
Blacktip shark	BOEM 9	Jun	2019	3	18	3
Blacktip shark	BOEM 9	Jul	2016	1	4	1
Blacktip shark	BOEM 9	Jul	2018	1	14	1
Blacktip shark	BOEM 9	Jul	2019	1	6	1

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
Blacktip shark	BOEM 9	Aug	2016	1	8	1
Blacktip shark	BOEM 9	Aug	2018	1	51	1
Blacktip shark	BOEM 9	Sep	2017	1	37	1
Blacktip shark	BOEM 9	Sep	2019	3	31	3
Blacktip shark	BOEM 9	Oct	2017	3	36	3
Blacktip shark	BOEM 9	Oct	2018	2	216	3
Blacktip shark	BOEM 9	Oct	2019	2	46	2
Sum	all	all	all	102	1688	110

D.9 White shark regional detections by year and month

Species	Year	Month	Individuals	Detections	Days
White shark	2016	03	1	19	1
White shark	2016	04	1	36	1
White shark	2016	06	1	13	1
White shark	2016	08	1	36	1
White shark	2016	11	2	22	3
White shark	2017	02	1	49	1
White shark	2017	05	1	13	1
White shark	2017	10	1	13	1
White shark	2017	11	1	92	1
White shark	2017	12	2	12	2
White shark	2018	04	2	15	2
White shark	2018	05	1	33	1
White shark	2018	10	1	10	1
White shark	2018	11	2	39	2
White shark	2018	12	1	4	1
White shark	2019	04	1	2	1
White shark	2019	06	1	20	1
White shark	2019	10	2	56	3
White shark	2019	11	1	3	1
White shark	2020	03	1	13	1
White shark	2020	04	1	1	1
White shark	2020	05	1	11	1

D.10 White shark detections by receiver site, month, and year

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
White shark	BOEM 10	Feb	2017	1	20	1
White shark	BOEM 10	Mar	2016	1	6	1

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
White shark	BOEM 10	Mar	2020	1	11	1
White shark	BOEM 10	Apr	2016	1	6	1
White shark	BOEM 10	May	2017	1	4	1
White shark	BOEM 10	May	2018	1	12	1
White shark	BOEM 10	May	2020	1	2	1
White shark	BOEM 10	Jun	2019	1	5	1
White shark	BOEM 10	Aug	2016	1	5	1
White shark	BOEM 10	Oct	2017	1	13	1
White shark	BOEM 10	Oct	2019	1	5	1
White shark	BOEM 10	Nov	2017	1	7	1
White shark	BOEM 10	Nov	2018	1	16	1
White shark	BOEM 11	Feb	2017	1	8	1
White shark	BOEM 11	Mar	2016	1	2	1
White shark	BOEM 11	Apr	2016	1	10	1
White shark	BOEM 11	Apr	2018	1	7	1
White shark	BOEM 11	May	2017	1	2	1
White shark	BOEM 11	May	2018	1	2	1
White shark	BOEM 11	May	2020	1	9	1
White shark	BOEM 11	Aug	2016	1	14	1
White shark	BOEM 11	Oct	2019	2	12	2
White shark	BOEM 11	Nov	2016	1	9	1
White shark	BOEM 11	Nov	2017	1	49	1
White shark	BOEM 11	Nov	2018	2	12	2
White shark	BOEM 11	Nov	2019	1	1	1
White shark	BOEM 12	Apr	2018	1	2	1
White shark	BOEM 12	Apr	2019	1	2	1
White shark	BOEM 12	Apr	2020	1	1	1
White shark	BOEM 12	Oct	2018	1	10	1
White shark	BOEM 12	Oct	2019	1	7	1
White shark	BOEM 12	Nov	2016	2	6	2
White shark	BOEM 12	Nov	2017	1	21	1
White shark	BOEM 12	Nov	2019	1	2	1
White shark	BOEM 12	Dec	2017	1	3	1
White shark	BOEM 12	Dec	2018	1	4	1
White shark	BOEM 7	Mar	2016	1	3	1
White shark	BOEM 7	Apr	2016	1	2	1
White shark	BOEM 7	Jun	2016	1	13	1
White shark	BOEM 7	Jun	2019	1	14	1
White shark	BOEM 7	Nov	2016	1	7	1
White shark	BOEM 7	Dec	2017	1	9	1

Species	Receiver Site	Month	Year	Individuals	Detections	Days/Month
White shark	BOEM 8	Feb	2017	1	4	1
White shark	BOEM 8	Mar	2016	1	5	1
White shark	BOEM 8	Mar	2020	1	1	1
White shark	BOEM 8	Apr	2016	1	3	1
White shark	BOEM 8	Apr	2018	1	6	1
White shark	BOEM 8	May	2017	1	1	1
White shark	BOEM 8	May	2018	1	4	1
White shark	BOEM 8	Jun	2019	1	1	1
White shark	BOEM 8	Oct	2019	2	8	3
White shark	BOEM 8	Nov	2017	1	8	1
White shark	BOEM 9	Feb	2017	1	17	1
White shark	BOEM 9	Mar	2016	1	3	1
White shark	BOEM 9	Mar	2020	1	1	1
White shark	BOEM 9	Apr	2016	1	15	1
White shark	BOEM 9	May	2017	1	6	1
White shark	BOEM 9	May	2018	1	15	1
White shark	BOEM 9	Aug	2016	1	17	1
White shark	BOEM 9	Oct	2019	2	24	2
White shark	BOEM 9	Nov	2017	1	7	1
White shark	BOEM 9	Nov	2018	1	11	1
Sum	all	all	all	67	512	68

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