Chapter 23: Incorporating temporal variation in seabird telemetry data: time variant kernel density models

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Acknowledgments: This chapter includes data from several collaborative field studies focused on the movement patterns of Red-throated Loons, Northern Gannets, and Surf Scoters in the Atlantic flyway, carried out by numerous principal investigators and agencies.

The work reported in this chapter constitutes part of two multi-year collaborative projects: 1) determining Offshore Use of Diving Bird Species in Federal Waters of the Mid-Atlantic United States Using Satellite Tracking, developed by the Bureau of Ocean Energy Management (BOEM) and the U.S. Fish & Wildlife Service (USFWS) and 2) the Atlantic and Great Lakes Sea Duck Migration Study, developed by the USFWS, Canadian Wildlife Service (CWS), and other state and federal partners. The first study was designed in partnership with the U.S. Geological Survey (USGS)-Patuxent Wildlife Research Center, Biodiversity Research Institute (BRI), and Memorial University of Newfoundland (MUN), and funded by BOEM, the Department of Energy (DOE; Award Number DE-EE0005362), BRI, MUN, and The Bailey Wildlife Foundation. The second project was primarily funded by the USFWS through the Sea Duck Joint Venture, DOE, and BOEM. In addition to these funding entities and the authors of this chapter, other partners that provided logistical or financial support include the Maryland Department of Natural Resources, Virginia Department of Game and Fisheries, University of Rhode Island, Delaware Division of Fish and Wildlife, and North Carolina Wildlife Resource Commission. The authors would also like to thank Dr. Scott Ford (Avian Specialty Veterinary Services), Dr. Glenn Olsen (USGS), Dr. Darryl Heard (University of Florida) and Stephane Lair and Ariane Santamaria-Bouvier (University of Montreal) for performing countless implant surgeries. We also thank Doug Howell (North Carolina Wildlife Resources Commission) for logistical support and area knowledge, Rob Hossler and Brian Rogers (Delaware Division of Fish and Wildlife) for logistical support and Stephen Earsom (USFWS) for aerial survey reconnaissance. We are indebted to Dr. Jim Woehr (BOEM), Jocelyn Brown-Saracino (DOE), and Scott Johnston, Caleb Spiegel, and Kirsten Luke (USFWS) for their assistance in project management. This report covers all data through the end of 2013, including the first two years of the BOEM/USFWS study and all prior years of the SDJV study.

Chapter 23 Highlights

Incorporating temporal variation into utilization distributions using seabird telemetry data: time variant kernel density models

Context[1]

Satellite telemetry is an effective tool for understanding individual animal movement patterns that can yield insight into habitat use over a species' spatio-temporal range. Chapters 20-22 explored spatial patterns and movement of three target species using satellite telemetry data: Red-throated Loon, Northern Gannet, and Surf Scoter. The utilization distribution approach applied in these chapters does not use the temporal component of the movement data in modeling animal habitat use, but rather collapses the data into a single period (defined by collaborators' identification of each individual's transition between life history stages). In this chapter, we explore the use of time variant kernel density models as a way to improve understanding of species' use of the landscape through time. A more data-intensive approach, focused on individual rather than group utilization distributions, is explored for Peregrine Falcons in Chapter 25.

Study goal/objectives

Incorporate temporal variation into kernel density models to 1) better understand space use through time, and 2) create utilization distribution maps at fine temporal scales, and generate movement videos.

Highlights

- Time variant kernel density maps proved to be an effective tool for showing fine-scale temporal variation in use of the study area.
- Analysis showed limited overlap of seabird habitat use with wind energy areas for the three species examined. The most overlap occurred for Northern Gannets.

Implications

Time variant kernel density models are an effective tool for generating dynamic maps (as video), demonstrating temporal variation in utilization distributions in the environment.

[1] For more detailed context for this chapter, please see the introduction to Part V of this report.

Abstract

A key component of the Mid-Atlantic Baseline Studies project was tracking the individual movements of focal marine bird species (Red-throated Loon [*Gavia stellata*], Northern Gannet [*Morus bassanus*], and Surf Scoter [*Melanitta perspicillata*]) through the use of satellite telemetry. This element of the project was a collaborative effort with the Department of Energy (DOE), Bureau of Ocean Energy Management (BOEM), the U.S. Fish and Wildlife Service (USFWS), and Sea Duck Joint Venture (SDJV), among other organizations. Satellite telemetry is an effective and informative tool for understanding individual animal movement patterns, allowing researchers to mark an individual once, and thereafter follow the movements of the animal in space and time. Aggregating telemetry data from multiple individuals can provide information about the spatial use and temporal movements of populations.

Tracking data is three dimensional, with the first two dimensions, X and Y, ordered along the third dimension, time. GIS software has many capabilities to store, analyze and visualize the location information, but little or no support for visualizing the temporal data, and tools for processing temporal data are lacking. We explored several ways of analyzing the movement patterns using the spatiotemporal data provided by satellite tags. Here, we present the results of one promising method: time-variant kernel density analysis (Keating and Cherry, 2009). The goal of this chapter is to demonstrate new methods in spatial analysis to visualize and interpret tracking data for a large number of individual birds across time in the mid-Atlantic study area and beyond. In this chapter, we placed greater emphasis on analytical methods than on the behavior and ecology of the animals tracked. For more detailed examinations of the ecology and wintering habitat use of the focal species in the mid-Atlantic, see Chapters 20-22.

Introduction

Van Winkle's (1975) seminal work on utilization distribution (UD) of animals has been variously adapted, but the basic two-dimensional probability surface showing space use for a period of time can overly simplify the dynamic structure of location data and the complexities of animal movements and spatial use. The utilization distribution, as defined by Van Winkle (1975), is simply a probability surface representing the habitat use of an animal throughout its home range, and is generated from location-based studies. Reducing point data to a UD has the advantage of estimating probability of use by an animal in areas where it has not been located, which can also be disadvantageous when assigning probability to an area where an animal does not occur (e.g., inland areas for marine birds). The kernel estimators are non-parametric in that there are no assumptions about the underlying distribution (Millspaugh et al., 2006; Seaman et al., 1999). The UD is dependent on sample size, however, and extrapolating UD to the population level may be biased by capture location and how well the sample of tagged animals represents the population of interest. In this study, we were unable to sample animals in an unbiased way, given the constraints of time and budgets. We were most interested in movements and habitat use along the mid-Atlantic coast of the U.S., however, and are hopeful that this capture bias did not negatively affect our estimates for this region. For Surf Scoters, where we captured birds in Québec and Labrador as well as in the mid-Atlantic region, we were able to confirm that there was negligible difference in winter use of the mid-Atlantic between these groups (A. Gilbert, unpub. data).

While we do have data for some Northern Gannets captured on the breeding grounds, these tags were short-lived and did not provide enough data to generate comparable UDs. Nevertheless, we pooled all data for each species irrespective of capture location.

In kernel based estimation of the UD, spatial smoothing parameters, $h_{xy,}$ in X (longitude) and Y (latitude) dimensions dictate the degree to which points contribute to the overall probability surface. These parameters extend the surface to the space between locations and beyond the edges of measured use, and appropriate assignment of h_{xy} is important for generating accurate UDs for the data. Thus, a larger value of h_{xy} will better account for uncertainty in the UD estimate, but can also smooth out any real small-scale variation in space use (Millspaugh et al., 2006). A variety of smoothing parameter estimation routines have been proposed, with various benefits among them (Millspaugh et al., 2006; Worton, 1989), but we do not examine their use here. Rather, we explore the kernel method for UD estimation to assess its usefulness in summarizing space use across the study area.

Typical two-dimensional UDs, generated to understand home ranges, collapses time into the estimate of the UD probability surface. This method simplifies the estimation of the surface, but reduces our ability to understand and demonstrate the temporal variability inherent in animal movements. Recently, Keating and Cherry (2009) extended the work of Van Winkle (1975) by adding time as another dimension by which to estimate UD. This extension to the basic time-insensitive UD can improve our understanding of migratory or other cyclical animal movements. Their approach uses a product kernel method (Silverman, 1986) with a wrapped Cauchy distribution for continuous circular variables, allowing kernel density estimation with Julian date as a circular time variable. The resulting time-variant kernel density model can represent the UD throughout the year, depending on the time in which the distribution is centered and the distribution's temporal bandwidth, h_t (time over which points are integrated to create a density surface). This temporal probability surface is analogous to the spatial probability surface governed in part by spatial bandwidth h_{xy}, but in the temporal dimension. Changing the size of h_t can have similar effects to that of UD estimates at the edge of the range, where animal use can be overestimated, depending on the size of the smoothing parameter (h_{xy}). Likewise, in the temporal dimension, this appears as lingering distribution during a time when animals may not actually occur. This is, in effect, a temporal smoothing on the spatial dimension that, if wide enough, results in a UD "ghosting" and an inaccurate representation of space use at that time. Unfortunately, the software used to calculate time-variant kernels does not have a method for estimating appropriate h_t; therefore, we explored multiple values for h_t to understand the model's sensitivity to h_t in the resulting maps.

Methods

Satellite telemetry data for focal species were collected from transmitters implanted in Red-throated Loons and Northern Gannets in the mid-Atlantic region (Delaware Bay, Chesapeake Bay, and Pamlico Sound), tags implanted in Surf Scoters by the SDJV elsewhere in eastern North America (see Chapter 20), and tail-taped tags on Northern Gannets from the colony at Cape St. Mary's, Newfoundland (see Chapter 22). Capture methods and locations, and PTT implantation methods, are discussed in Chapters 20-22. Satellite data were compiled and filtered using the Douglas Argos Filter[2] (DAF; Douglas et al.,

[2] http://alaska.usgs.gov/science/biology/spatial/douglas.html

2012). The DAF is a threshold filter that has several user-defined parameters to flag improbable locations in satellite tracking data. The parameters are adjustable based on species' movement behaviors, time of year, and the scale of the area under observation. With the DAF, data are retained if they pass a spatial redundancy test and/or a movement rate and turning angle test. Since our bird data contain both short-distance, local movements, and long-distance migratory events, we employed a hybrid of the distance, angle, and rate (DAR) filter, and the minimum redundant distance (MRD) filter. Using DAF, we also identified the best representative point per duty cycle for each animal, to reduce redundant daily positional information and spatial-autocorrelation. We used the best point per duty cycle in all estimations of time-variant UD. We aggregated all data across years within species (2000-2013 for Surf Scoter, and 2012-2013 for all others) for this analysis. We chose to include points from all years for all birds, to represent the variability in spatial use regardless of whether that variation was between animals or years.

The resulting output files from DAF were processed in R version 3.1.2 (R Core Team, 2014) for modeling and mapping. We subsampled locations using the package 'adehabitatHR' version 0.4.12 (Calenge, 2006) for modeling the UDs. We filtered data from implanted birds to exclude the first two weeks of data, to reduce the effects of implantation surgery on movement, and to exclude those that transmitted for fewer than 30 days. To reduce the "temporal ghosting" effect inherent in this method, in which any location where an animal has been recorded is identified as a possible current use area, we binned location data by 60 day intervals over the annual cycle. For each time interval, we selected a random sample of locations from each individual to prevent animals with large numbers of locations from disproportionately influencing the resulting pooled UD. The size of each resample was determined by the lower quartile (or fewer) of the number of locations available for all animals (see Table 23-1). We derived a composite estimate of the kernel UDs using a bootstrapping procedure. For each species, we resampled locations from all animals and calculated the UD for the resample. The resampling procedure was repeated for 100 iterations and the bootstrapped mean and standard error surface served as the composite UD for each time interval.

The likelihood cross-validation procedure that was used by Keating and Cherry (2009) was not implemented in the R package 'adehabitatHR' version 0.4.12 (Calenge, 2006). Therefore, we subjectively chose an appropriate bandwidth to suit the data. We used temporal bandwidth h_t=0.05, and spatial bandwidths h_{xy}=0.25. Values of h_t could vary between 0-1, but without good guidance on appropriate values for this smoothing parameter, smaller values generally produced results that better represented the actual movement and distribution patterns of the animals. However, more work is needed to explore this parameter. Spatial bandwidth was also subjectively explored in this exercise, but we found that the smoothing parameter of 0.25 was reasonable without losing multimodal detail of high use areas or extending the probability surface into areas where animals are unlikely. There are other objective methods for determining the spatial bandwidth not implemented here (Millspaugh et al., 2006), but it has also been suggested that there are many situations where subjective selection of h_{xy} is appropriate (Kie et al., 2010).

Map production was accomplished in R using package 'OpenStreetMap' version 0.3.1 (Fellows and Stotz, 2013) to create background maps and package 'raster' version 2.3 (Hijmans, 2015) to crop the UDs to exclude over-land areas and overlay the UD output on each background map. Videos of the sequence of time variant kernel maps were produced in mp4 format using the open-source audio-video editing software Ffmpeg[3]. We generated maps and corresponding videos for each focal species scaled to the mid-Atlantic Outer Continental Shelf (the study area of the BOEM telemetry project, which extends from the New York Bight to the South Carolina border, and fully encompasses the mid-Atlantic study area described in other chapters of this report). Twenty-four static maps were produced, eight for each species (Figure 23-1 to Figure 23-12). Maps include overlays of the mid-Atlantic study area, BOEM renewable energy leasing areas, wind planning areas, and wind energy areas[4] (collectively referred to hereafter as Wind Energy Areas, or WEAs), and mid-Atlantic capture locations.

Results and discussion

The time-variant kernel density maps depict broad movement patterns throughout the year (see Figure 23-1 to Figure 23-12) and do an excellent job revealing the temporal patterns of movement throughout the mid-Atlantic study area and beyond. The "temporal ghosting" effect inherent to this method, in which any location where an animal had been recorded was identified as a possible current use area, was limited by the use of a 60-day moving time window around each date. The small temporal bandwidth (h_t=0.05) also reduced the effect of apparent occupancy in an area during a period when they do not occur. We were able to determine a reasonable h_t parameter by running a series of models with decreasing temporal bandwidth. The challenge was to smooth data temporally over the period of estimation, but not to the extent that the kernel density model was homogenized across the entire time period (in a sense removing the temporal component) such that we lost temporal detail of occurrence in the kernel density maps. This was an inexact method which we hope to explore more objectively, e.g., likelihood cross-validations estimators used by Keating and Cherry (2009). Similarly, we used a subjectively determined spatial bandwidth (h_{xy}=0.25), which was also determined by running a series of model runs while changing h_{xy}. We arrived at the h_{xy} used in this work because it provided a more realistic continuous surface while not generating the "spurious structure" warned against by Keating and Cherry (2009). Again, we plan to explore a more objective method for bandwidth estimation, such as the likelihood cross-validations estimator.

Red-throated Loons

The Red-throated Loons tracked in this study wintered primarily in bays and relatively nearshore areas of the mid-Atlantic, with the UD largely focused near initial capture locations. Areas of highest use in January-April were in Delaware Bay, Chesapeake Bay, and Pamlico Sound (Figure 23-1 and Figure 23-2). Birds began migrating north in April-May, with a migratory stopover area apparent offshore of Cape Cod, Massachusetts in May (Figure 23-2). Birds began returning to the mid-Atlantic by November, to spend the non-breeding period in the region where they had been captured the previous winter (Figure 23-4). There was little apparent overlap between UDs and WEAs, with loons remaining largely inshore of these areas. For a more detailed discussion of the movement and habitat use of tracked Red-throated Loons, see Chapter 21.

[3] http://ffmpeg.org/
[4] http://www.boem.gov/Renewable-Energy-GIS-Data/

Northern Gannets

In winter, Northern Gannets ranged much farther than the other focal species, moving from Cape Cod to well south of the study area, primarily staying nearshore and somewhat around large bays, particularly at the mouths of Chesapeake and Delaware Bays (Figure 23-5 to Figure 23-6). Spring migration began in April with birds returning from southern locations, moving north to Cape Cod (Figure 23-6). Birds began arriving back in the study area and points south by November (Figure 23-8). At this time, Northern Gannets were most widely dispersed. From the maps, it is clear that there is the potential for Northern Gannet UDs to overlap WEAs, particularly off of Delaware and New Jersey, but primarily birds appear to be inshore of these areas. For a more detailed discussion of the movement and habitat use of these tracked Northern Gannets, see Chapter 22.

Surf Scoters

Like Red-throated Loons, Surf Scoters wintered in bays and nearshore, primarily Chesapeake Bay, Delaware Bay, Pamlico Sound, and off of Cape Cod (Figure 23-9 to Figure 23-10). Spring movements north began in April and extended into May. However, some Surf Scoters remained in the Chesapeake Bay area as late as May (Figure 23-10). By November, most Surf Scoters had returned to mid-Atlantic wintering areas (Figure 23-12). There was very little overlap between the UD and WEAs, the birds being primarily inshore of these areas, though it is important to note the potential bias introduced by the sampling design, as noted in the Introduction. Specifically, some wintering areas may be under-represented by including Surf Scoters marked in the mid-Atlantic study areas, particularly those wintering areas located further north in the Gulf of Maine. Comparisons of UDs calculated separately for birds captured within and outside of the study area suggest, however, that this potential bias is unlikely to be affecting our conclusion about overlap between the UD and WEAs. For a more detailed discussion of the movement and habitat use of these tracked Surf Scoters, see Chapter 20 and a recent seaduck migration study report by the Seaduck Joint Venture (SDJV, 2015).

Utility of time-variant wildlife data for offshore wind energy planning

Spatiotemporal movement patterns are difficult to portray with static maps that represent entire years or seasons, but when depicted as an animation, using shorter time-steps, the life-history [or temporal migratory] connections of these animals are revealed. This was not easily accomplished prior to the advent of satellite telemetry tags and the more sophisticated computer modeling techniques. We believe that this technique has great utility in depicting complex spatiotemporal patterns not immediately obvious in multiple static maps. The time-variant kernel method allowed us to bring temporal information into our estimation of the density surface depicting utilization distributions. Normal kernel density estimation methods collapse the temporal dimension, losing some of this important detail. We believe this method has great potential for understanding and visualizing the annual cycles of these species.

Understanding the temporal variation in animal movements and habitat use is essential for minimizing the effects of offshore wind energy development on wildlife populations. For example, certain development activities may be timed to minimize impacts to potentially vulnerable populations in those locations, or possible mitigation strategies can be targeted to life history periods of greatest need. This type of temporal data is a key component of Strategic Environmental Assessments (SEA) in Europe and

Environmental Impact Assessments (EIS) in the United States (Allison et al., 2008; Fox et al., 2006). All three focal species in this satellite telemetry study are of conservation interest to the USFWS, specifically in relation to offshore wind energy development (ACJV, 2008; USFWS, 2008), and we expect that these data will be useful to both regulators and developers as the offshore wind energy development expands in the United States.

Literature cited

[ACJV] Atlantic Coast Joint Venture, 2008. New England/Mid-Atlantic Coast Bird Conservation Region (BCR 30) Implementation Plan, Atlantic Coast Joint Venture.

Allison, T.D., Jedrey, E., Perkins, S., 2008. Avian Issues for Offshore Wind Development. Mar. Technol. Soc. J. 42, 28–38. doi:10.4031/002533208786829115

Calenge, C., 2006. The package "adehabitat" for the R software: A tool for the analysis of space and habitat use by animals. Ecol. Modell. 197, 516–519. doi:10.1016/j.ecolmodel.2006.03.017

Douglas, D.C., Weinzierl, R., C. Davidson, S., Kays, R., Wikelski, M., Bohrer, G., 2012. Moderating Argos location errors in animal tracking data. Meth. Ecol. Evol. 3, 999–1007. doi:10.1111/j.2041-210X.2012.00245.x

Fellows, I., Stotz, J.P., 2013. OpenStreetMap: Access to open street map raster images. R package version 0.3.1.

Fox, A.D., Desholm, M., Kahlert, J., Christensen, T.K., Krag Petersen, I., 2006. Information needs to support environmental impact assessment of the effects of European marine offshore wind farms on birds. Ibis (Lond. 1859). 148, 129–144. doi:10.1111/j.1474-919X.2006.00510.x

Hijmans, R.J., 2015. Raster: geographic data analysis and modeling. R package version 2.4-15.

Keating, K.A., Cherry, S., 2009. Modeling utilization distributions in space and time. Ecology 90, 1971–1980. doi:10.1890/08-1131.1

Kie, J.G., Matthiopoulos, J., Fieberg, J., Powell, R. a, Cagnacci, F., Mitchell, M.S., Gaillard, J.-M., Moorcroft, P.R., 2010. The home-range concept: are traditional estimators still relevant with modern telemetry technology? Philos. Trans. R. Soc. Lond. B. Biol. Sci. 365, 2221–31. doi:10.1098/rstb.2010.0093

Millspaugh, J.J., Nielson, R.M., McDonald, L., Marzluff, J.M., Gitzen, R.A., Rittenhouse, C.D., Hubbard, M.W., Sheriff, S.L., 2006. Analysis of Resource Selection Using Utilization Distributions. J. Wildl. Manage. 70, 384–395. doi:10.2193/0022-541X(2006)70[384:AORSUU]2.0.CO;2

R Core Team, 2014. R Development Core Team. R A Lang. Environ. Stat. Comput.

[SDJV] Seaduck Joint Venture, 2015. Atlantic and Great Lakes Sea Duck Migration Study: progress report June 2015, 2015.

Seaman, D.E., Millspaugh, J.J., Kernohan, B.J., Brundige, G.C., Raedeke, K.J., Gitzen, R.A., 1999. Effects of sample size on kernel home range estimates. J. Wildl. Manage. 63, 739–747. doi:10.2307/3802664

Silverman, B., 1986. Density estimation for statistics and data analysis, Chapman and Hall. doi:10.2307/2347507

[USFWS] U.S. Fish and Wildlife Service, 2008. Birds of Conservation Concern 2008. Arlington, Virginia.

Van Winkle, W., 1975. Comparison of Several Probabilistic Home-Range Models Webster Van Winkle. J. Wildl. Manage. 39, 118–123.

Worton, B.J., 1989. Kernel methods for estimating the utilization distribution in home range studies. Ecology 70, 164–168.

Figures and tables

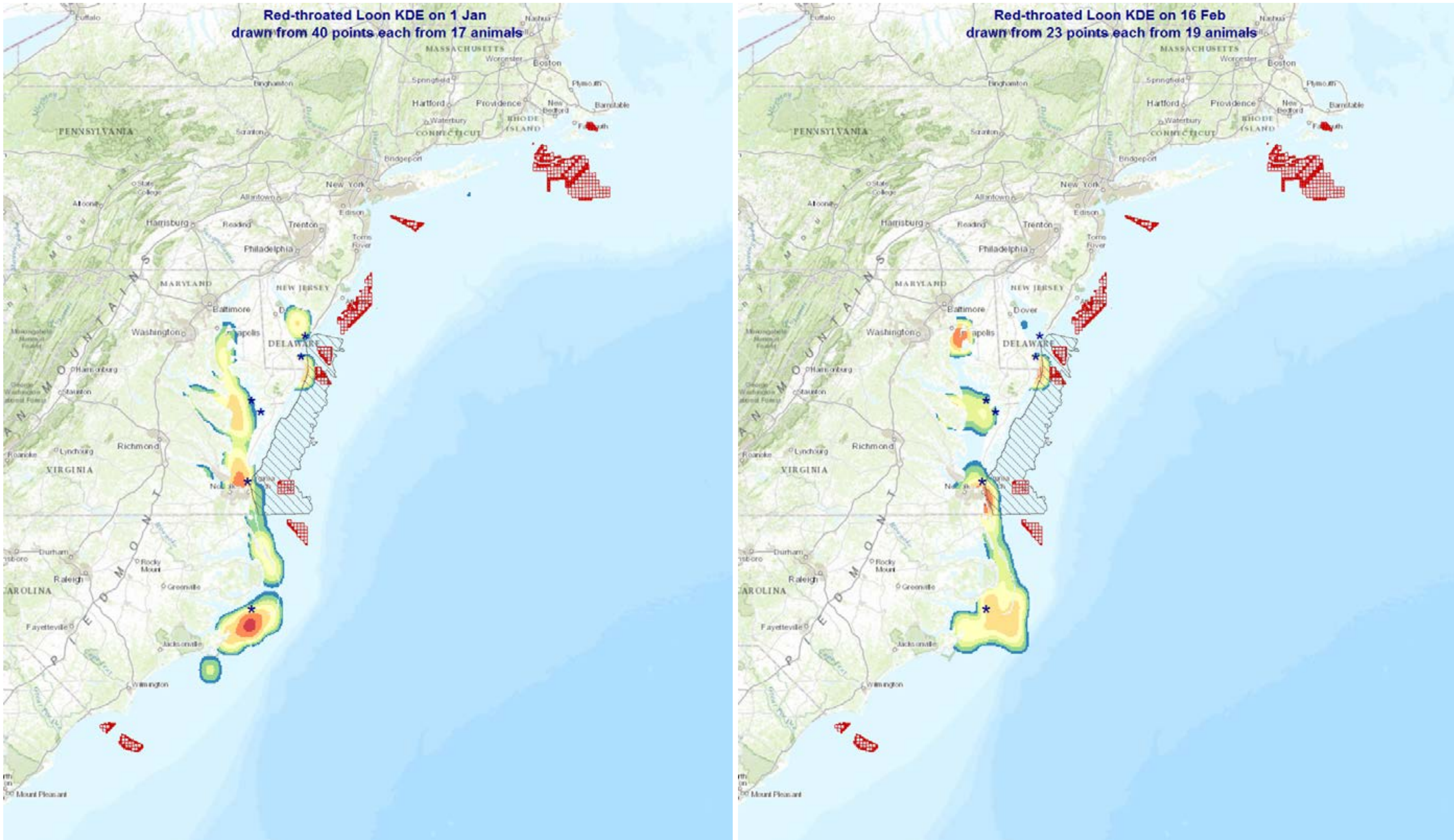

Figure 23-1. Time variant kernel density (KDE) maps for Red-throated Loons on January 1 (left) and February 16 (right) for 2012-2013 in the mid-Atlantic study area. Forty points from 17 animals (left) and 23 points from 19 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

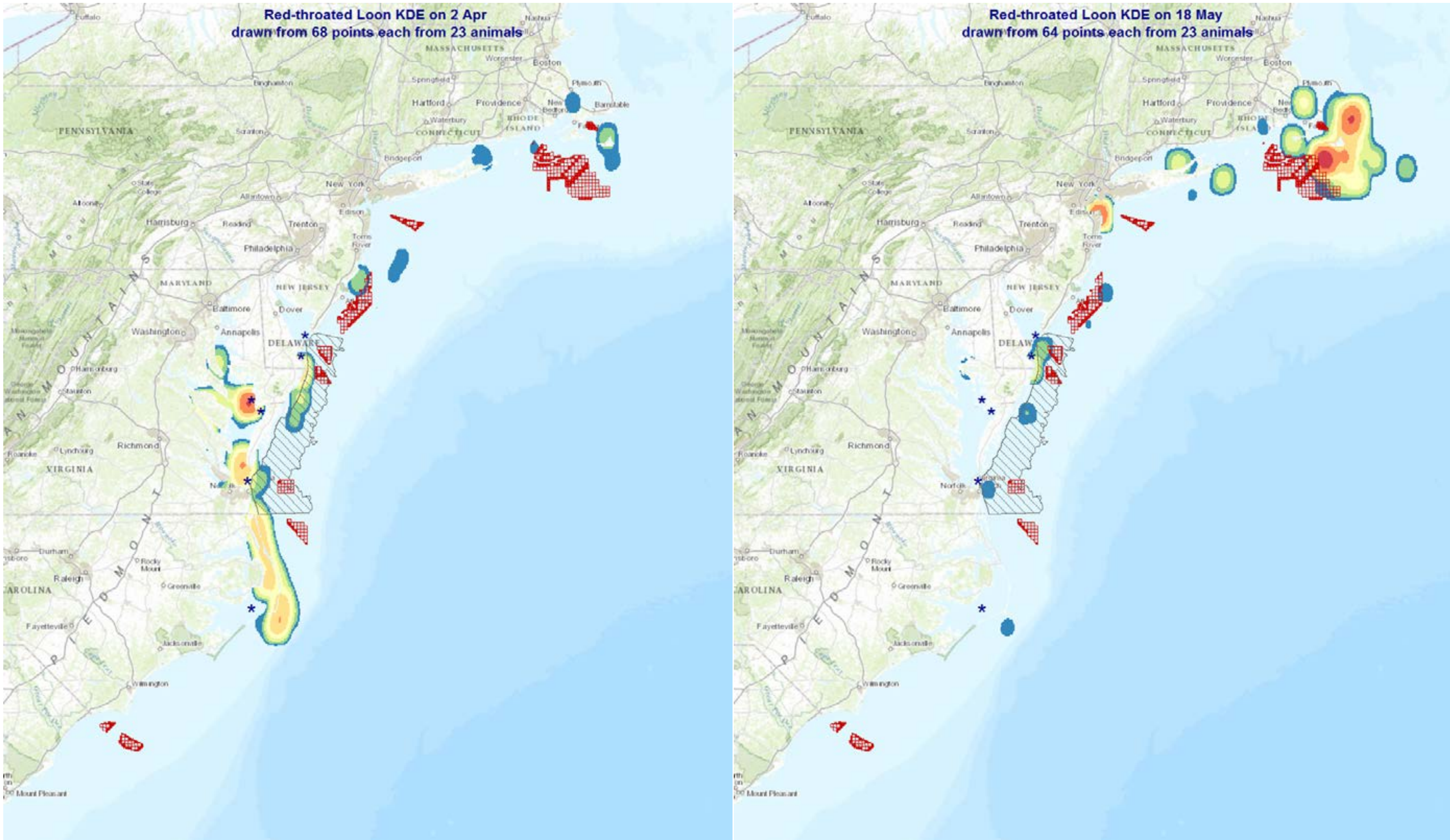

Figure 23-2. Time variant kernel density (KDE) maps for Red-throated Loons on April 2 (left) and May 18 (right) for 2012-2013 in the mid-Atlantic study area. Sixty-eight points from 23 animals (left) and 64 points from 23 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

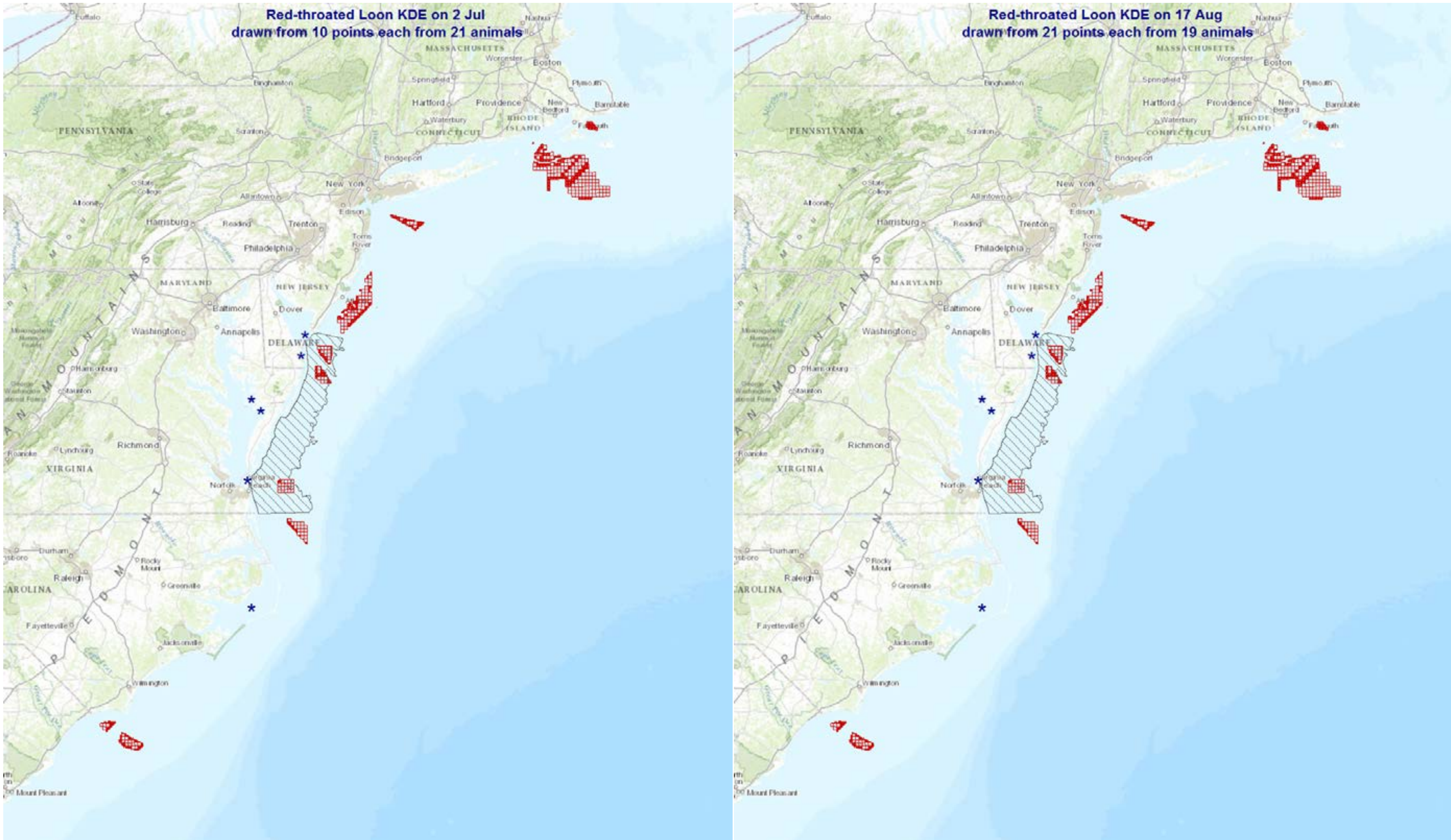

Figure 23-3. Time variant kernel density (KDE) maps for Red-throated Loons on July 2 (left) and August 17 (right) for 2012-2013 in the mid-Atlantic study area. Ten points from 21 animals (left) and 21 points from 19 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

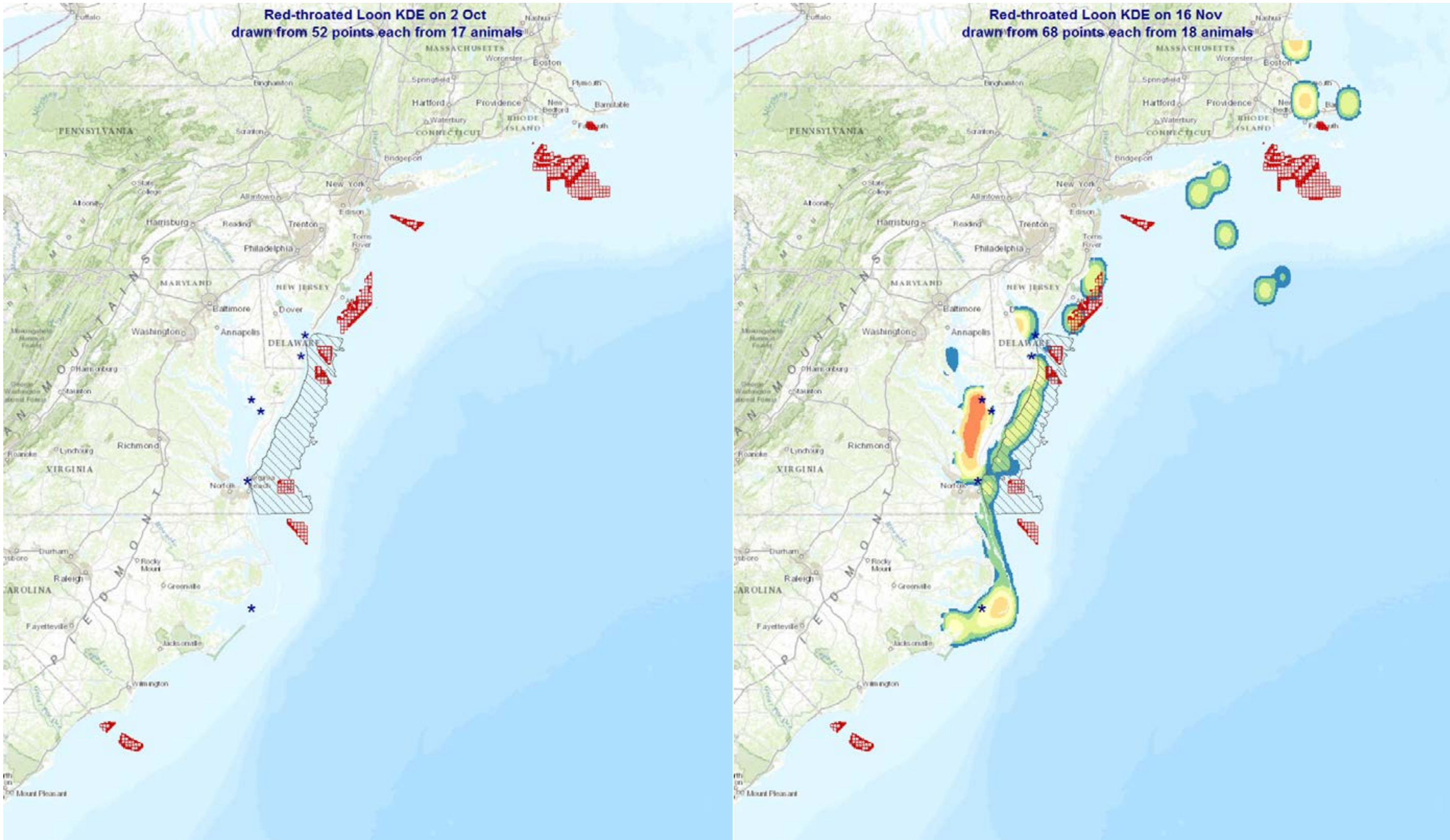

Figure 23-4. Time variant kernel density (KDE) maps for Red-throated Loons on October 2 (left) and November 16 (right) for 2012-2013 in the mid-Atlantic study area. Fifty-two points from 17 animals (left) and 68 points from 18 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

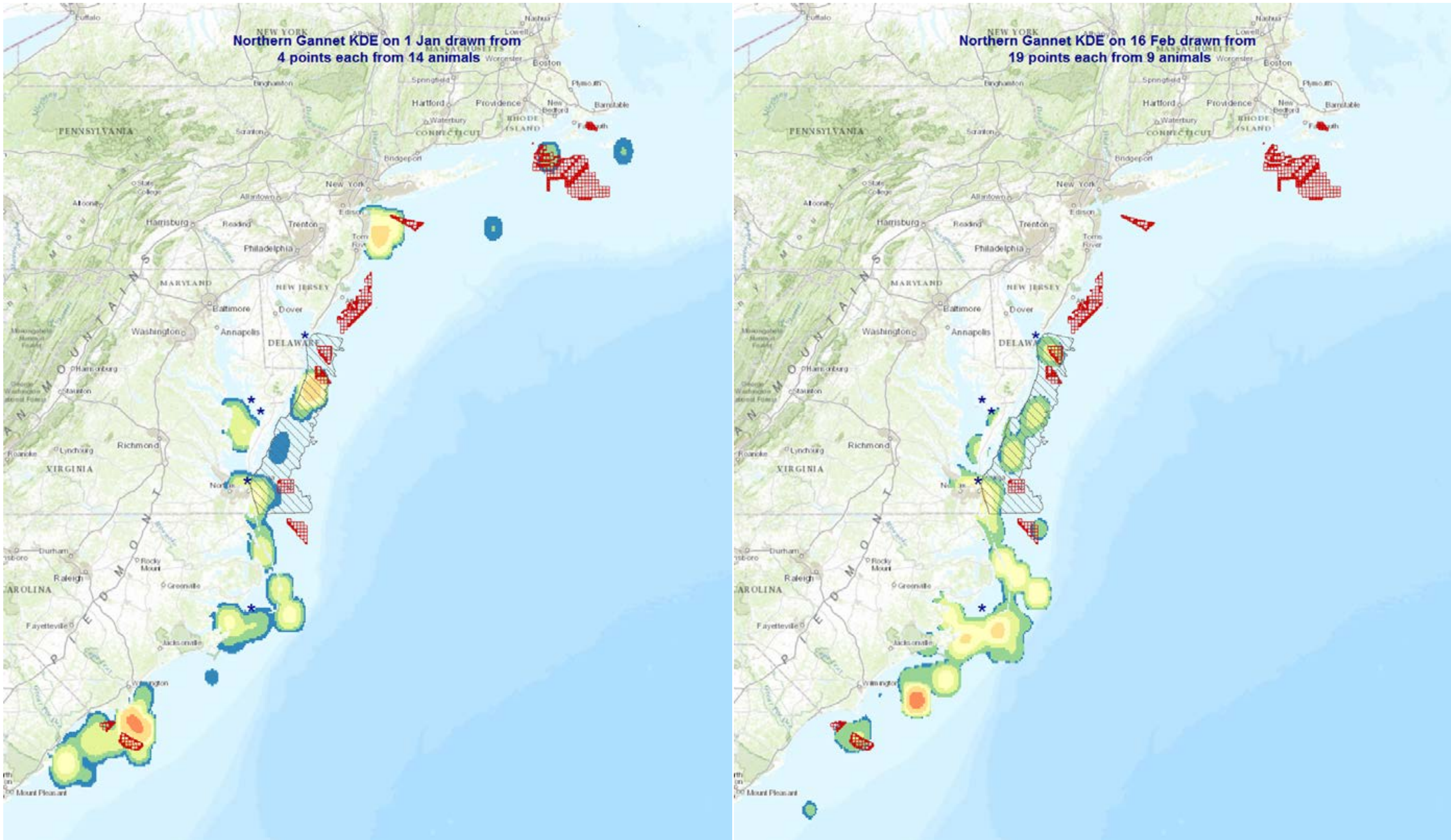

Figure 23-5. Time variant kernel density (KDE) maps for Northern Gannets on January 1 (left) and February 16 (right) for 2012-2013 in the mid-Atlantic study area. Four points from 14 animals (left) and 19 points from 9 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

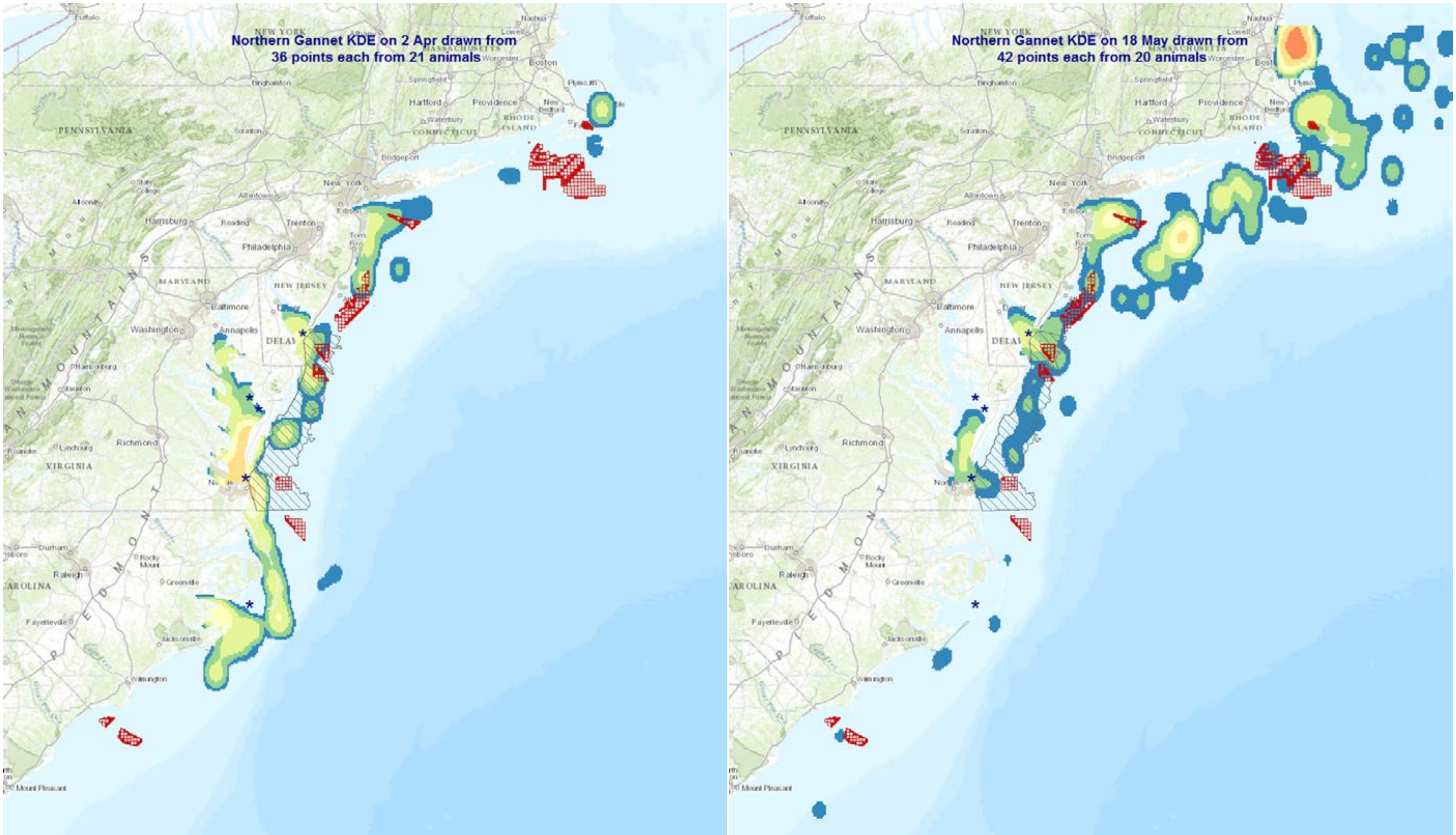

Figure 23-6. Time variant kernel density (KDE) maps for Northern Gannets on April 2 (left) and May 18 (right) for 2012-2013 in the mid-Atlantic study area. Thirty-six points from 21 animals (left) and 42 points from 20 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

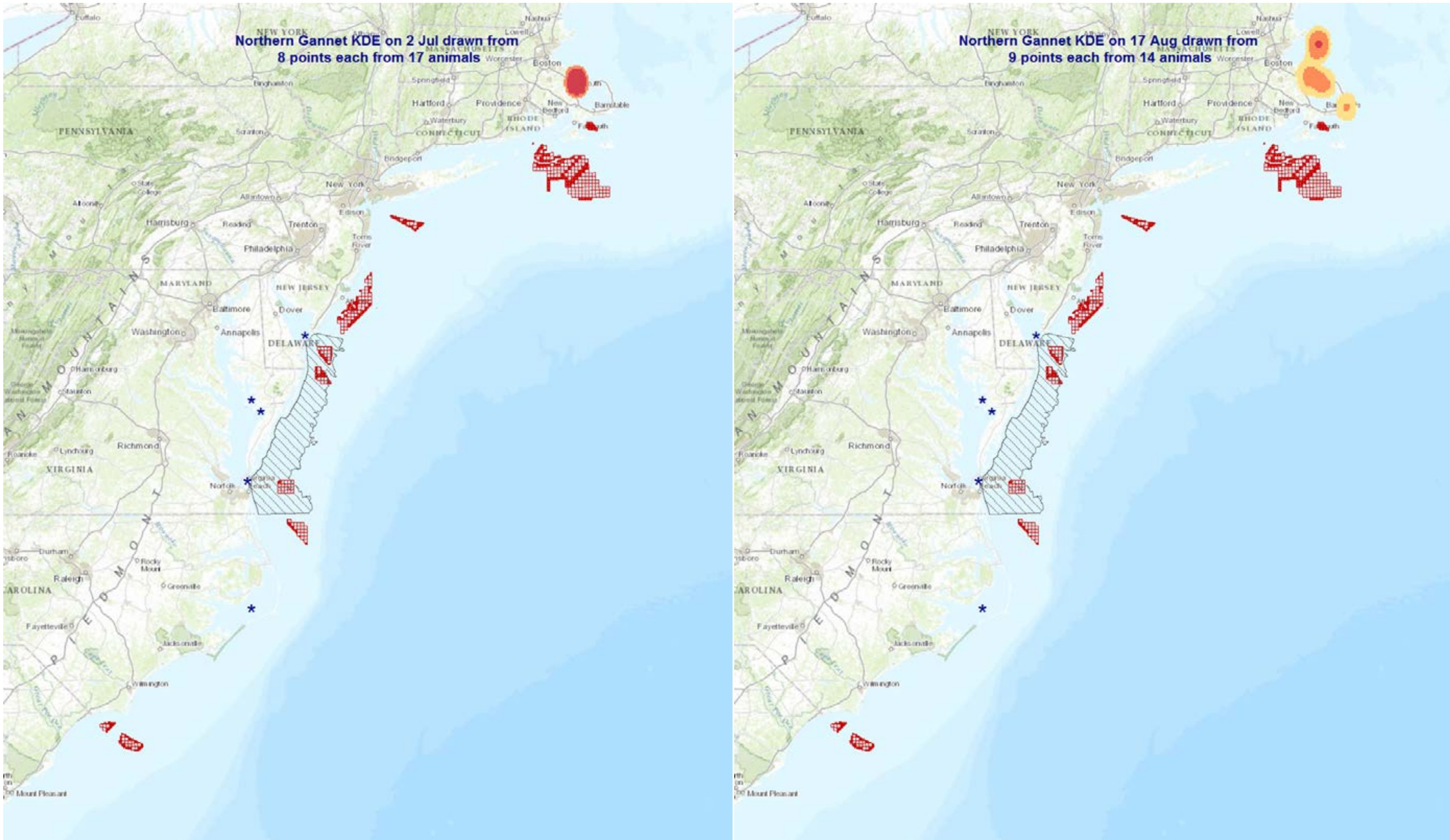

Figure 23-7. Time variant kernel density (KDE) maps for Northern Gannets on July 2 (left) and August 17 (right) for 2012-2013 in the mid-Atlantic study area. Eight points from 17 animals (left) and 9 points from 14 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

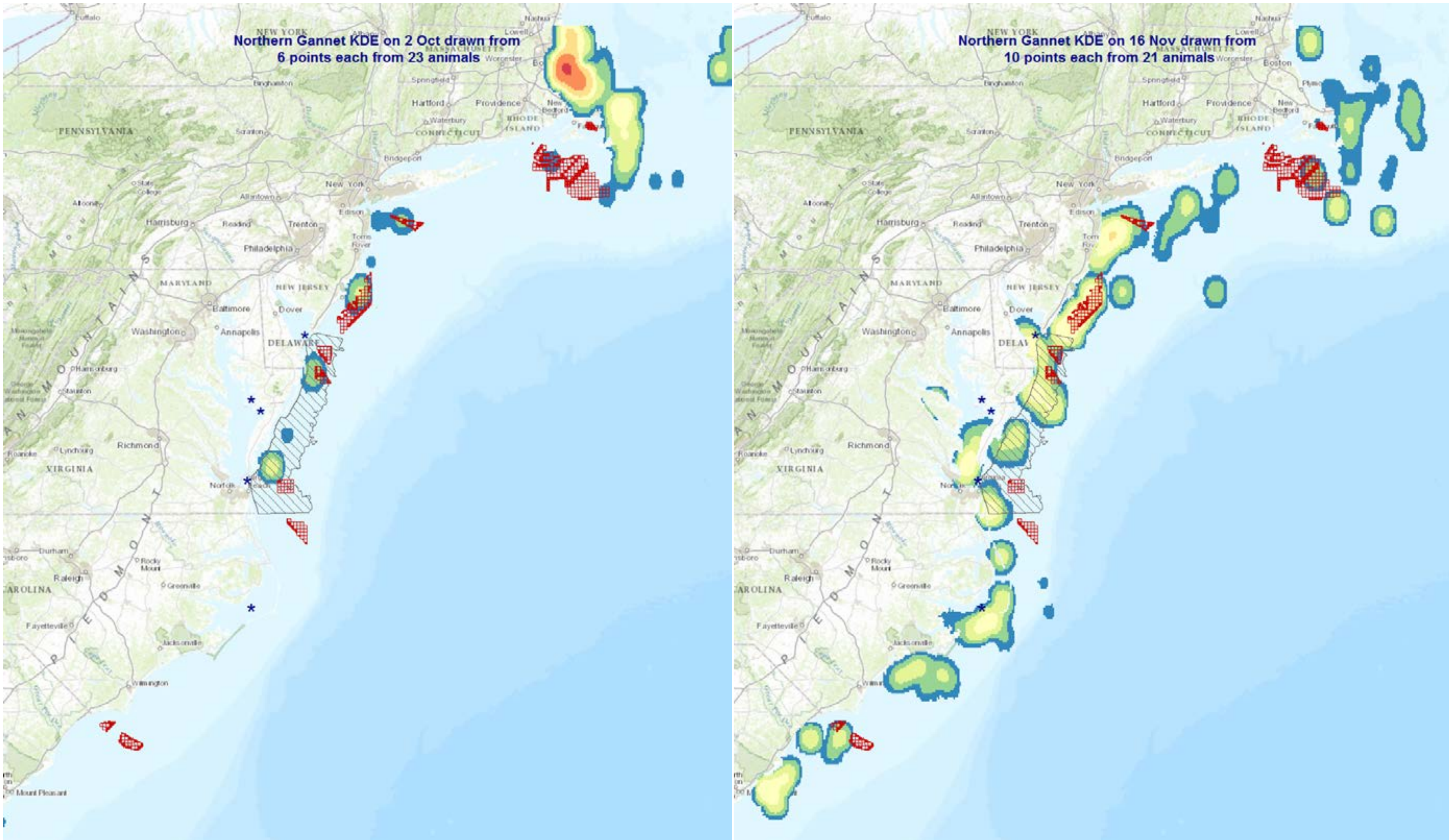

Figure 23-8. Time variant kernel density (KDE) maps for Northern Gannets on October 2 (left) and November 16 (right) for 2012-2013 in the mid-Atlantic study area. Six points from 23 animals (left) and 10 points from 21 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

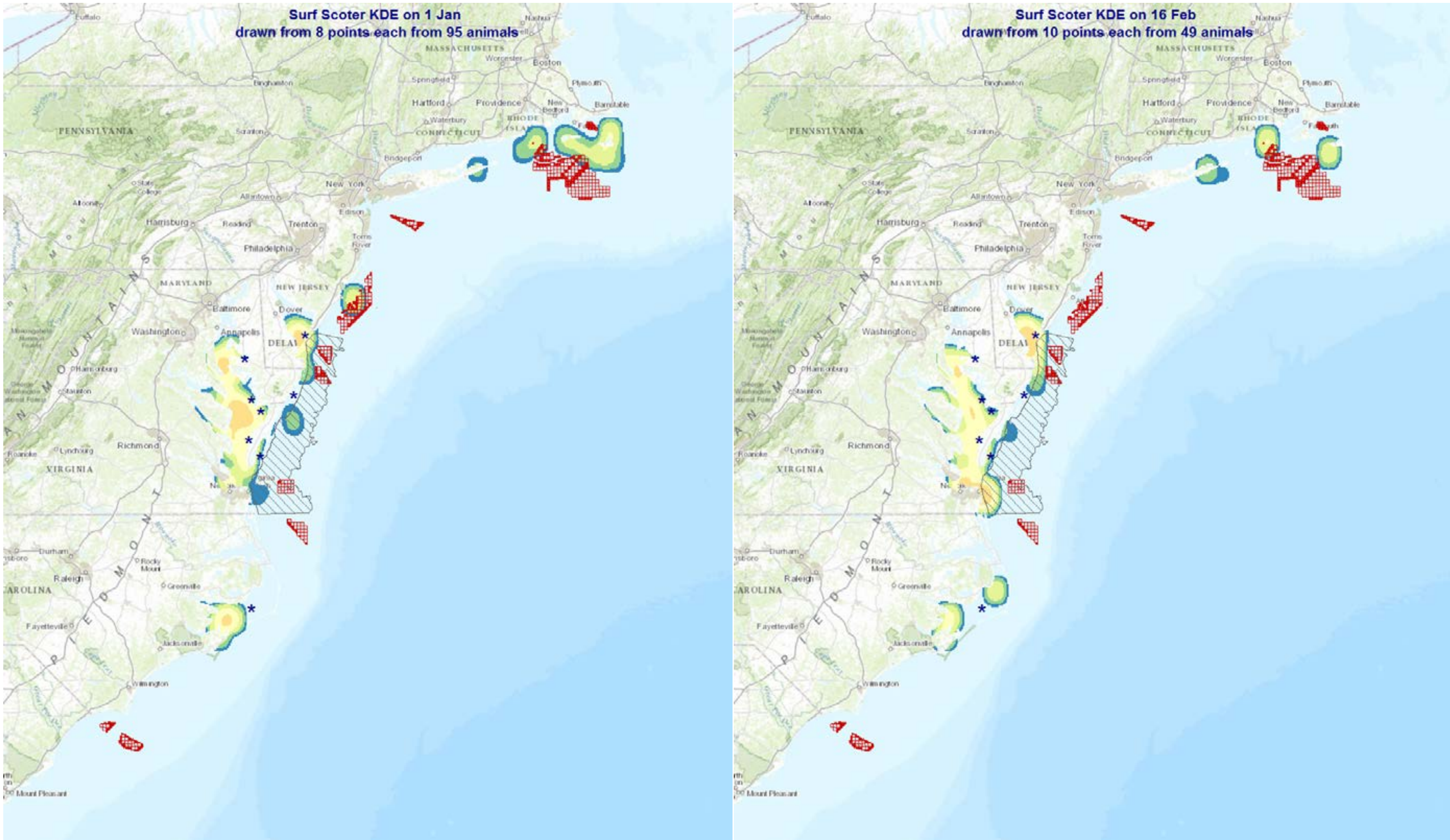

Figure 23-9. Time variant kernel density (KDE) maps for Surf Scoters on January 1 (left) and February 16 (right) for 2012-2013 in the mid-Atlantic study area. Eight points from 95 animals (left) and 10 points from 49 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

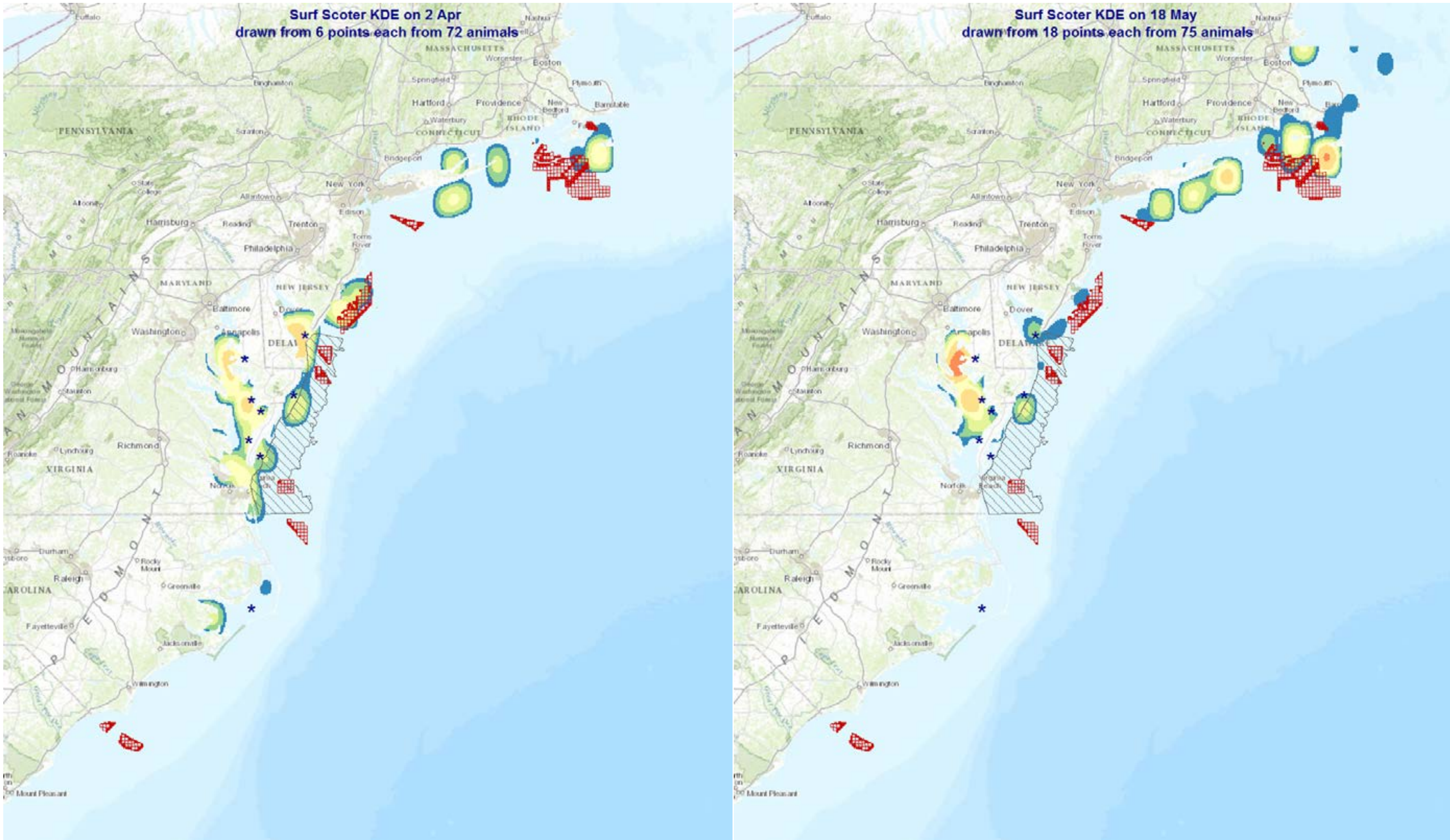

Figure 23-10. Time variant kernel density (KDE) maps for Surf Scoters on April 2 (left) and May 18 (right) for 2012-2013 in the mid-Atlantic study area. Six points from 72 animals (left) and 18 points from 75 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

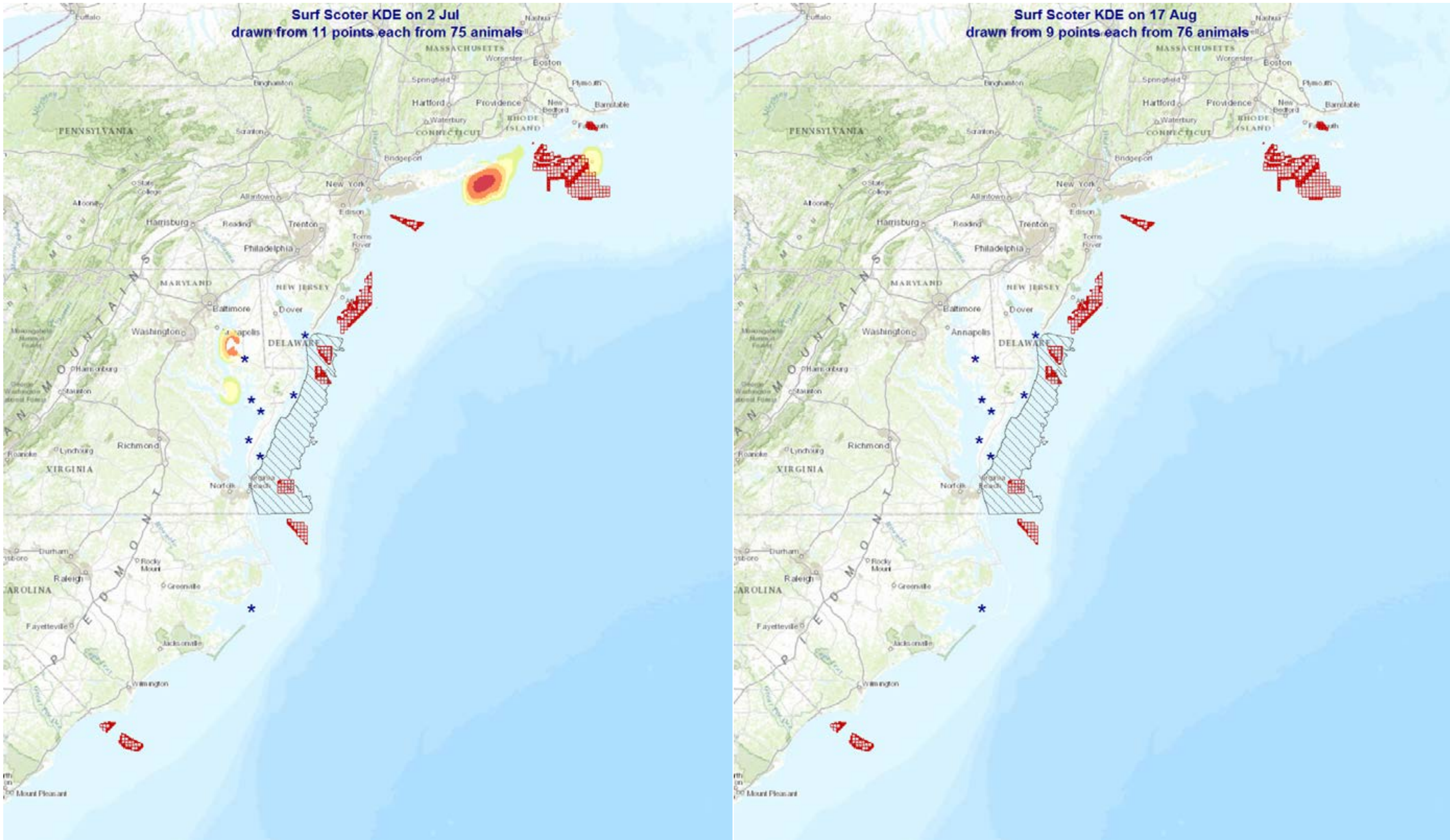

Figure 23-11. Time variant kernel density (KDE) maps for Surf Scoters on July 2 (left) and August 17 (right) for 2012-2013 in the mid-Atlantic study area. Eleven points from 75 animals (left) and 9 points from 76 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

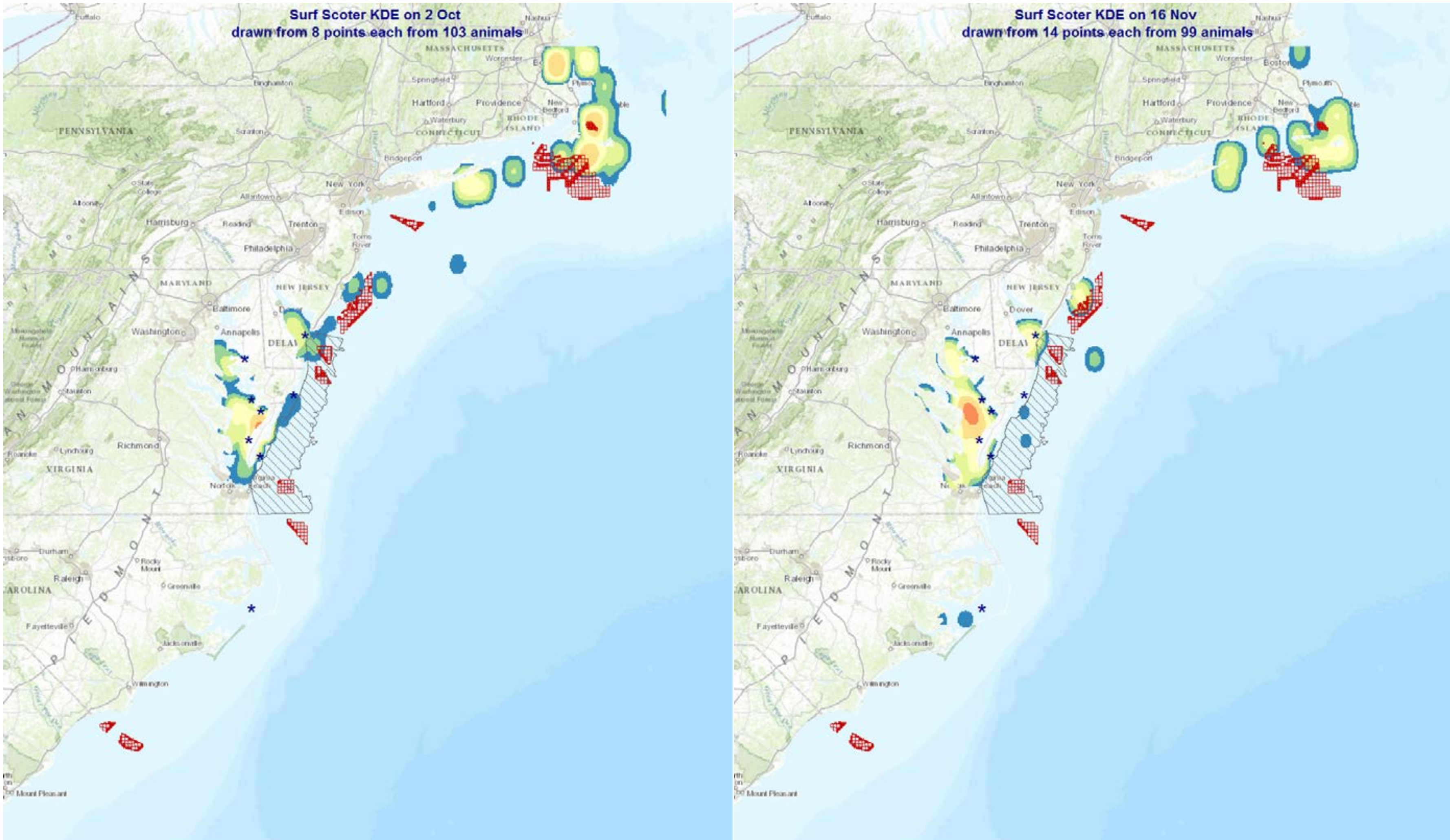

Figure 23-12. Time variant kernel density (KDE) maps for Surf Scoters October 2 (left) and November 16 (right) for 2012-2013 in the mid-Atlantic study area. Eight points from 103 animals (left) and 14 points from 99 animals (right) were used for calculating the composite KDEs for these dates. Composite KDE is depicted in quantile gradations from lowest (blue) to highest (red) probabilities of use. The mid-Atlantic study area is in light gray, the BOEM WEAs in red, and capture locations are indicated by blue asterisks.

Table 23-1. Number of animals and (samples sizes per individual) on each date the time variant kernel was estimated. Samples sizes are the number of locations for each animal used in the composite kernel estimates.

Date	Red-throated Loon	Northern Gannet	Surf Scoter
January 1	17 (40)	14 (4)	95 (8)
February 16	19 (23)	9 (19)	49 (10)
April 2	23 (68)	21 (36)	72 (6)
May 18	23 (64)	20 (42)	75 (18)
July 2	21 (10)	17 (8)	75 (11)
August 17	19 (21)	14 (9)	76 (9)
October 2	17 (52)	23 (6)	103 (8)
November 16	18 (68)	21 (10)	99(14)