GoM PAM – A robust passive acoustic marine mammal density monitoring program in the Gulf of Mexico

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Summary

We propose a long-term, robust program for monitoring the density of offshore (i.e., oceanic and continental shelf) marine mammal stocks in the US waters of the Gulf of Mexico. The program is based on deployment of retrievable autonomous bottom-moored passive acoustic recorders, some of which would be located at permanent monitoring stations and others relocated periodically to increase spatial coverage. Additional sensors would be deployed at a subset of the stations, allowing ranging of detected vocalizations and hence calculation of the species-specific area monitored around each station. In addition, a parallel program of tagging would be initiated enabling calculation of species-specific vocalization rates.

Taken together, the program would provide:

- robust and precise estimates of species density year-round at a monthly temporal resolution;
- long-term population trends;
- the inputs required to build stock-specific spatial- and spatio-temporal models of habitat preference.

There is the potential to co-locate other sensing devices along with the passive acoustic mooring sites. An example is upward-looking active acoustic plankton, fish and cephalopod sensors. The stations could thereby become a key part of an integrated ocean observing system.

This proposal is only an outline. The next step is to convene a working group to develop a comprehensive plan that would include taxonomic, geographic and temporal scope, target precision, required sample size, suggested deployment locations, recommended hardware, suggested management structure and approximate budget. A pilot phase will be required before the design is finalized and main program initiated.

Recommendation: A working group be formed to develop a comprehensive plan for a passive acoustic marine mammal density monitoring program in US offshore waters of the Gulf of Mexico, including a pilot study.

1 Background

The Gulf of Mexico (GoM) is home to 21 species of marine mammal. For US waters, these species are divided by NOAA into 57 stocks (i.e., independent monitoring units), comprising:

- 31 bottlenose dolphin stocks from Bay, Sound and Estuaries;
- 3 bottlenose dolphin stocks in coastal waters (0-20m depth);
- 1 bottlenose dolphin and 1 Atlantic spotted dolphin stock in continental shelf waters (20-200m depth);
- 21 species in oceanic waters (>200m depth) including endangered sperm whales, 3 species of beaked whale, the Gulf Bryde’s whale (proposed to be listed as endangered), dwarf and pygmy sperm whales, and a wide diversity of subtropical and temperate dolphin species.

Obtaining accurate and precise estimates of population size and trend for each of these stocks is key to determining stock status, including recovery from the Deepwater Horizon oil spill and effect of any future large-scale pollution event. In addition, if density estimates are available at suitable spatial and temporal scales, they can be used in species habitat models to enhance our understanding of environmental drivers of species distribution.

We focus here on offshore (i.e., continental shelf and oceanic) stocks (inshore stocks require a different approach to monitoring that we do not discuss here). Current population monitoring for offshore stocks throughout US waters is undertaken by NOAA using visual line transect surveys from a ship or airplane. While this is a well-established methodology, it is very costly, and thus comprehensive population surveys are carried out only infrequently. For example, in the GoM, dedicated comprehensive visual surveys have been carried out only 3 times: in 2003-4, 2009 and 2017-19. Visual methods are potentially inefficient for marine mammal species that spend much of their time underwater and hence out of sight. By contrast, many of these species regularly make vocalizations that are detectable underwater over large distances. This has stimulated interest in development of density estimation methods based on passive acoustic detection, using a variety of platforms including towed arrays behind survey ships, autonomous gliders, drifting buoys, and retrievable bottom-mounted sensors. As an example, the most recent GoM NOAA surveys include a towed hydrophone array in the ship-based (oceanic) stratum.

Here, we focus on passive acoustic monitoring (PAM) using static, bottom-mounted sensors because they have proven to be effective and are relatively cost-efficient. Consideration of other platforms should be part of a more rigorous survey design exercise, and part of ongoing potential adaptation of an operational monitoring program. Bottom-mounted sensors could be deployed year-round, offering the potential for fine temporal-scale monitoring of marine mammal populations including robust seasonal estimates of density at a variety of spatial scales.

2 Passive acoustic monitoring of Gulf of Mexico Species

A complete survey design exercise will need to consider our knowledge of the distribution and acoustic biology of the target species, our ability to detect and classify each species’ vocalizations and the ranges these sounds may be heard over given the seasonal acoustic environment within the study region. In addition, the design should, where possible, build upon the acoustic monitoring that has already taken place in the GoM. A very brief overview is given here; a more comprehensive review (including of mobile platforms and tag-derived data) is given by Latusek-Nabholz et al. (2017) and Frasier et al. (In press).

From the acoustic perspective there are, broadly speaking three functional groups of offshore stocks: (1) one species of baleen whale (Bryde’s whale), which produces a variety of low-frequency (<1 kHz vocalizations) (Širović et al. 2013); (2) a group of deep-diving odontocetes (sperm whales, dwarf and pygmy sperm whales, and beaked whales) that produce short-duration, directional, broadband, high frequency echolocation clicks mostly at depth; and (3) a group of shallower-diving small delphinid odontocetes that produce echolocation clicks as well as longer-duration, omnidirectional frequency-modulated tonal signals known as whistles.

PAM studies of ambient noise have been undertaken in the Gulf since at least 1996 (see review in Latusek-Nabholz et al. 2017). Marine mammal studies are more recent, and include the following efforts using autonomous bottom-moored sensors.

- Duty-cycled recordings at sample rates between 8-20 kHz were obtained using Cornell University’s Marine Autonomous Recording Units (MARUs) at 7 sites from 2010-2012.
- Relatively short duration (several month) continuous broadband recordings by Environmental Acoustic Recording System (EARS) buoys were made by the Littoral Acoustic Demonstration Center-Gulf Ecological Monitoring and Modeling Consortium (LADC-GEMM), focused on five fixed sites within the Mississippi Canyon and Mississippi Valley region during various times between in 2001, 2002, 2007, 2010, 2015, 2016, and 2017. Since 2007 a subset of sites had multiple buoys for ranging purposes. The sampling rates varied, with the highest being 192 kHz, starting in 2007.
- Continuous broadband recordings (with some gaps) were made at up to six sites using High-frequency Acoustic Recording Packages (HARPs) sampling at 200 kHz during the period 2010-2016. These were deployed by researchers at Scripps Institution of Oceanography in collaboration with the Center for the Integrated Modeling and Analysis of the Gulf Ecosystem (C-IMAGE) consortium, the NRDA, and NOAA.
- A set of five EARS and five Rockhoppers (updated versions of the MARU), and a Woods Hole Oceanographic Institution (WHOI) single multi-depth tetrahedral array have been deployed in the Mississippi Canyon region in 2018 and 2019, in a pilot GoM baseline monitoring project sponsored by BOEM and led by HDR Inc.
- In a study led by NOAA South-East Fisheries Science Center, five HARPs were deployed from 2016-2017 on the continental shelf in the NE Gulf with the specific aim of monitoring Bryde’s whale.

3 Key general design principles for population monitoring

Some guidelines for a robust long-term wildlife population monitoring program were given by Thomas et al. (2004). They include the following.

1. A clear statement of objectives, including a statement of desired precision of quantities monitored at stated spatial and temporal scales.
2. Robust estimates of absolute (not relative) density.
3. Adequate spatial sampling, possibly using a “panel” design, where some of the sampling locations are repeated every year (assuming an annual time frame for sampling) and others rotated in and out to increase spatial coverage.
4. Rigorous data quality control, open data access, engagement of a scientific steering committee, regular program review and commitment to production of peer-reviewed publications to help maintain quality and expose the program to new ideas.
5. Flexibility to incorporate improved methods and technology.

The second and third points are worth emphasizing in the context of passive acoustic monitoring (PAM).

Aiming to monitor absolute density is important because relative density estimates, also called indices of density, often do not provide reliable estimates of population trend. Examples of indices for PAM surveys are counts of detections per unit time, or of presence-absence of detections within a given time window. As an example of what can go wrong, Helble et al. (2013) found that call detections of humpback whale song units at monitoring sites off Southern California generally increased over a two year period, but that the range-specific probability of detecting calls also increased (due to changes in shipping) and that when the index was corrected for this change in detection probability no pattern was apparent. This issue is well known in the ornithological literature, where even completely standardized counts can lead to different trends from the estimated trends in density (see, e.g., Norvell et al. 2009). Although estimating absolute abundance from PAM data is difficult, we believe that the closer once can come to this goal, the less likely the resulting monitoring program is to give biased estimates of population trend.

Fixed passive acoustic sensors are not the ideal for achieving good spatial replication, compared with alternative platforms that move, such as sensors towed from active platforms such as vessels or gliders, or drifting buoys. On the other hand, such platforms present their own problems: active platforms are expensive, gliders are largely unproven for estimating absolute density, and drifting buoys are susceptible to sampling bias since they sample non-random locations. Ongoing research is addressing many of these problems (e.g., for gliders and drifters, see Harris et al. 2019), and therefore a complete evaluation of monitoring programs should include evaluation of these platforms. However, here we focus on fixed sensors because they are known to work for this application. What constitutes “adequate” or “good” in terms of spatial replication is hard to define without more design effort – in particular, a study of the expected precision of estimates relative to the monitoring goals (e.g., Booth et al. 2017). However, as an example, Buckland et al. (2001) recommend a minimum of 10-20 spatial replicates for reliable estimation of spatial variance, and it seems likely that a rather higher number of samples will be required for acceptable precision; we suggest that in the first instance (and pending an investigation of sample size as a function of precision), 30 sampling locations be considered to be an absolute minimum.

The spatial positioning of the sensors has a strong influence on how the data can be analyzed, and on the reliability of the results. Random spatial sampling ensures that the measured trends are representative of the region within which the sampling takes place. However, simple random sampling is inefficient, because sensors can, by chance, be located close to one another and hence sample the same habitat. A better design is to use a systematic grid, randomly positioned, or a space-filling (Johnson et al. 1990) or spatially balanced design (e.g., Generalized Random Tessellation Stratified (GRTS) sampling, Stevens and Olsen 2004). In all these cases, the measured trends are guaranteed to be (on average) representative of the region because of the properties of the design; this is called design-based inference. An alternative is to use model-based inference, where a statistical model is fitted to the observed data, and this model is then used to predict the trend over the region. The model may be a function of spatially- and/or temporally-referenced habitat covariates, such as bathymetry, temperature, distance from shore, ocean current, etc. In model-based methods, random sampling is not required, although the samples should cover the full range of covariate values present in the region; otherwise the results are unlikely to be reliable. Random designs (especially the efficient ones mentioned above) are therefore ideal for model-based inference and have the additional advantage that the simpler design-based inference is also possible as a first step. Model-based inference is not guaranteed to be unbiased (results are only as good as the model) but offers the possibility of understanding the observed patterns in a way not possible with design-based methods. A full discussion of model-based vs design-based inference is given by Thompson et al. (2012), and in the specific context of density and abundance estimation of wildlife population by Borchers et al. (2002).

There is a natural tension in design of long-term monitoring programs between the desire for fixed sampling sites, which gives best precision for estimating trends (Thomas et al. 2004), and allocating new sites each sampling period (e.g., year), which gives best spatial coverage. A compromise, unless sample size is large enough that spatial coverage is good with fixed sites alone, is a type of panel design, where some sites are permanent, and others sampled using some kind of rotation scheme (e.g., Lavrakas 2008).

It may be desired to maintain at least some of the already-established monitoring sites while increasing spatial replication. While this is not strictly compatible with a design-based monitoring strategy, with a sufficient number of randomly-located supplemental sites any bias will be low (plus a model-based analysis is always possible). This is somewhat similar to the panel design mentioned above.

Assuming a design with some element of randomization is chosen, it is important to be able to account for locations that cannot be sampled. For example, in some parts of the Gulf, there are many oil pipelines and platforms, and bottom-mounted acoustic sensors cannot be anchored in their close vicinity. Systematic grid designs are somewhat inflexible in this respect; the solution adopted by the SAMBAH passive acoustic survey of harbor porpoise in the Baltic Sea (Carlen et al. 2018) was to have ready a secondary grid of locations nested within the primary grid, and to randomly choose a nearby secondary location if the primary was not feasible. Space filling designs are more flexible, in the sense that areas that cannot be surveyed can be excluded from the space where samplers are allocated within. For both types of design, it is also helpful to have a rule that allows the sampling location to be moved by a small amount (a few hundred meters, perhaps) to avoid localized sensitive areas. A space-filling design was used in locating sensors used in the BOEM-sponsored project in the Mississippi Canyon region that was mentioned above.

4 Passive acoustic density estimation

As stated in the previous section, reliable monitoring requires repeated robust estimates of spatial density within the defined monitoring area. A review of passive acoustic density estimation is given by Marques et al. (2013). They present a generic (“canonical”) formula for density estimation:

$$\hat{D} = \frac{n\left(1-\hat{f}\right)}{\hat{p}a\hat{r}}$$

where D is the animal density (number of animals per unit area), n is the number of “objects” (for example animal vocalizations of the target species) counted, f is the proportion of false detections, p is the probability of detecting an object within area a, and r represents other multipliers that convert object density to animal density. Probably the most popular method for a given species involves counting acoustic detections from that species over a given time period; in this case, r is the “cue rate”, the number of vocalizations produced by an average animal over that time period. (Hence this method is sometimes referred to as “cue counting”.) A detailed discussion of methods in the context of passive acoustic density monitoring is given by Booth et al. (2017). To summarize, density estimation boils down to five key components:

- deciding on the object to count – typically individual animal vocalizations, but in some contexts it may be individual animals (uniquely identifiable from their calls), animal dives (sometimes identifiable from calling patterns), or animal groups;
- obtaining a reliable count (n) of objects in the study area over a given time period – this is typically a problem of adequate spatial replication;
- estimating the false positive rate ($1-f$) – typically this is relatively straightforward, requiring hand validation of a sample of automatically-processed acoustic recordings;
- estimating the detection probability (p) – typically a challenging problem (see below);
- estimating the cue production rate (r) – another challenging problem (see below).

4.1 Detection probability

There are broadly two approaches for estimating detection probability: auxiliary measurement and acoustic modelling (see review by Marques et al. 2013). In the former, additional measurements are taken (preferably at the same time and place as the monitoring survey) that are informative about detection probability; in the latter, assumptions are made about the distribution of vocal animals, animal sound source levels, sound propagation and detector characteristics and these are used to infer detection probability. Note that even the former approach requires assumptions (e.g., about distribution of animals in the vicinity of the sensors), but these are much less demanding. Overall, we believe more robust results will be obtained by measuring detectability, where possible, rather than relying on acoustic model results, and hence we focus in this section on the measurements required and associated analysis approaches.

There are a variety of approaches for estimating detection probability based on additional data collection. Marques et al. (2013) and Booth et al. (2017) review the current options, and point out the most appropriate one depends on the type of additional data it is possible to collect. The emphasis in Booth et al. (2017) is on practical solutions for long-term monitoring programs, and they focus on two methods, derived from standard (non-acoustic) density estimation approaches: distance sampling (specifically, point transect) and spatially-explicit capture recapture (SECR, also often called spatial capture recapture SCR). Both are also explained in Marques et al. (2013) and we refer readers to these two articles for details. The two have different data requirements. Distance sampling is designed for a “sparse array” of sensors, where the sensors are in general too far apart for detections of the same object to be made on multiple sensors at once. In this circumstance, the key piece of additional information required to estimate detection probability, p, is the horizontal distance to each detection (hence the sensors in the sparse array must be capable of estimating range, or at least some must). SECR, on the other hand, is designed for a “dense array”, where the same object is routinely detected on more than one sensor and, further, it is possible to know that this is the same object (i.e., to associate the object across sensors). An example is where vocalizations are the object being counted, and the same vocalization is detected on multiple hydrophones. Additional information such as time of arrival of the sound, bearing, and received level can be usefully incorporated if they are available, to produce estimates with better precision (Borchers et al. 2015, Stevenson et al. 2015). Apart from distance sampling and SECR, other approaches are possible (Marques et al. 2013), but do not appear to be so well suited to long-term monitoring.

In multi-species surveys, a hybrid approach may be possible, where sensors are spaced on a grid such that they form a dense array for some species whose sounds propagate further, but are a sparse array for other species (and therefore require some ranging sensors for the distance sampling approach). Additional temporary sensor arrays may also be deployed, either as part of the main monitoring program or auxiliary studies by researchers (e.g., validation studies).

Note that it is not essential that all sensors contribute to estimating detection probability, so long as there are a sufficient number that do so detection probability estimated from these sensors is representative of all sensors. Hence, when there is a large amount of spatial replication, some cost savings may be made by only collecting detectability information at a subset of the sensors. The cost to precision of trend estimates may not be high as uncertainty in detection probability may not be a large component of overall variance. Booth et al. (2017) have designed a simulation tool to explore these issues.

Bringing the above themes together, we give a conceptual illustration of a systematic spatial array in Figure 1.

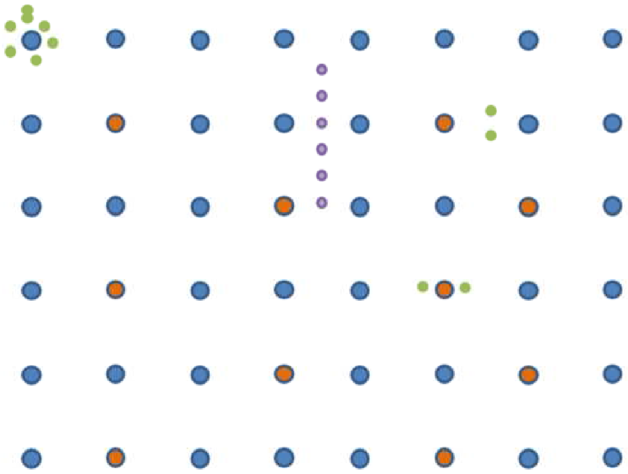

Figure 1. Example hybrid design for more multi-species acoustic monitoring, with different sensor types. Blue indicates standard sensors, orange ranging-capable sensors, green temporary sensors dedicated to small scale studies/experiments, and purple temporary sensors involved in specific sound propagation experiments/calibrations. Reproduced from Marques et al. (2017).

4.2 Cue rate

In situations where the object being counted is a vocalization (a "cue") then an estimate of the population average cue rate is required, averaged over the smallest space and time unit we wish to make inference over. There is, at best, only partial information about cue rates in the PAM data: even when individual animals can be tracked acoustically using a sophisticated acoustic array, we only obtain information about cue rate while the animal is vocalizing often enough for tracking to take place, and close enough to the sensor array. Hence, to get an unbiased estimate of cue rate, a separate study, typically using animal-borne acoustic tags, is needed.

We acknowledge that obtaining cue rates for all target species is a very challenging undertaking. It may be that the monitoring program would start without the ability to do this for many species, and this element gets added as our ability to measure cues improves with new tagging methods and other technological developments.

5 Preliminary design for Gulf of Mexico

To illustrate the above-discussed ideas, we present a preliminary design for the acoustic component of a Gulf of Mexico monitoring program. We do not suggest the design for estimating cue rate. The suggestion below is not intended to prejudice a working group tasked with coming up with a real-world design, which will no doubt be rather different from this – it is merely for illustration and discussion.

We assume that marine mammal trends will be required at the spatial resolution of the BOEM planning area (Figure 2), as well as overall. (Other alternatives would be to stratify by acoustic region (Figure 2 of Latusek-Nabholz et al. 2017) or bathymetry.) We anticipate that spatio-temporal modelling of the data will also, in the longer term, produce the ability for much finer scale resolution on species trends. Exact monitoring program goals would need to be determined as an integral part of any planning of a final design.

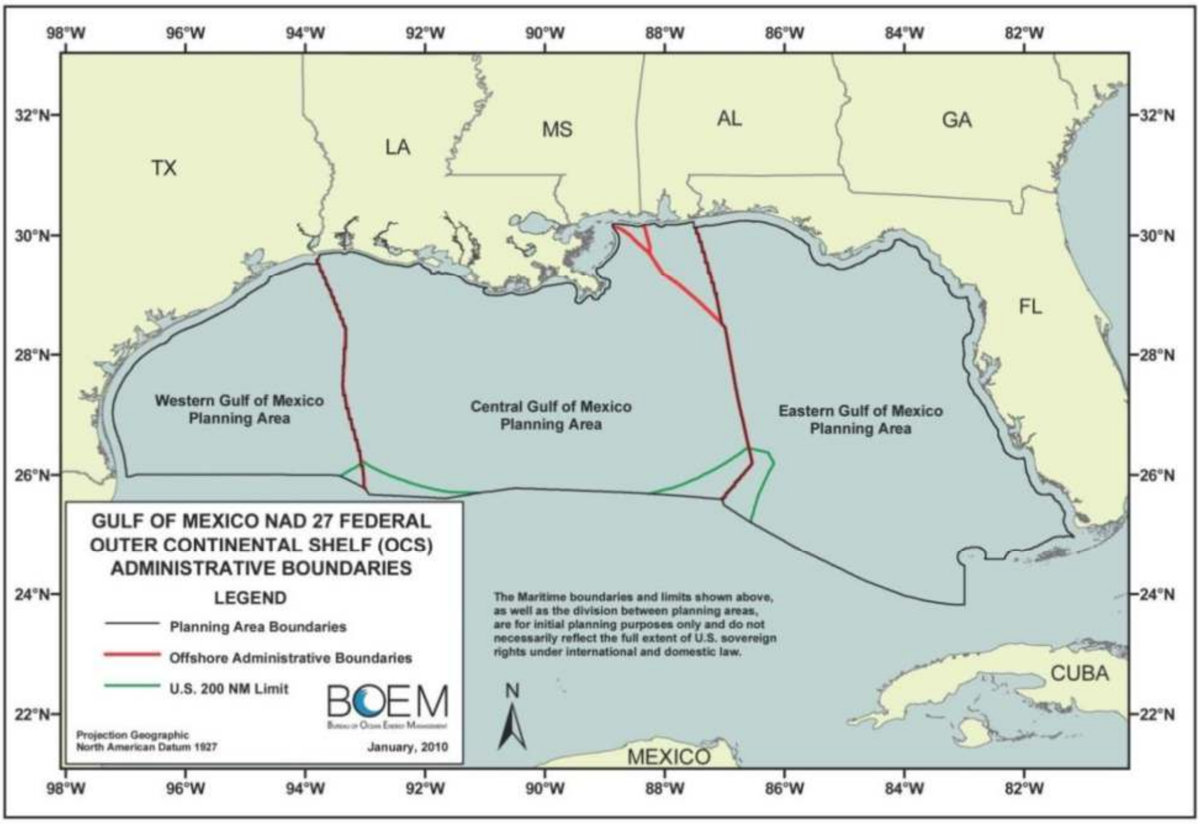

Figure 2. Assumed Gulf of Mexico monitoring area, including planning area boundaries (black polygons) used in the 2007-2012 Five Year Plan. Source: https://www.boem.gov/uploadedFiles/BOEM/Oil_and_Gas_Energy_Program/Mapping_and_Data/Administrative_Boundaries/Gulf_Plan.pdf *(accessed 12th July 2019)*

In this design, as a demonstration of what is possible, we suggest maintaining five of the previously-used long-term monitoring sites – here we chose those more-or-less arbitrarily, but there would need to be a careful discussion of criteria for inclusion. In addition, we suggest 40 monitoring sites, each of which is surveyed every second year (so 20 per year). Of the 25 sites monitored each year (5 monitored every year and 20 every other year), 7-8 sites per year (moving between years) would have acoustic hardware deployed that is capable of deriving range to detected vocalizations, while the rest that year would be simpler single-sensor setups. We do not specify at this stage how the ranging might take place, but examples might be bottom-mounted tetrahedral hydrophone arrays, deployed a suitable distance apart, or one or more vertical arrays.

Depending on the monitoring goals, it may be feasible to duty cycle the sensors, so that they are for example collecting acoustic data one quarter of the time, and so deployments may be for up to a year at a time.

In this example (Figure 3), we have employed a space-filling design, where points are selected from a random set of candidate locations in such a way as to minimize a “coverage criterion” based on sum of distances between all points (Johnson et al. 1990). An alternative would be a systematic grid of points, but this makes it harder to incorporate existing sites, if it were desired to retain these.

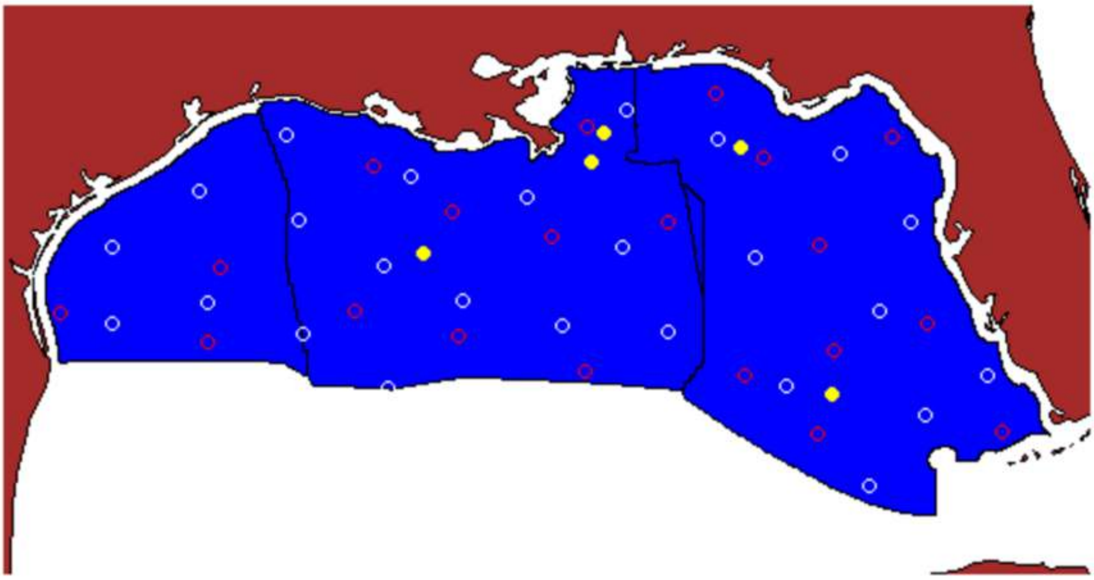

Figure 3. Example realization of a spatially balanced design, with 2 sets of 20 random locations (red and white open circles) added to 5 of the sites that have been used in previous monitoring studies (closed yellow circles). Each set of 20 locations could be surveyed in alternate years, with the 5 previously monitored sites being surveyed in all years. Further (or alternative) previously-monitored sites could also be included in the design. Blue regions represent planning areas – note that these are slightly different from those in Figure 2 because they are the 2012-2017 Final Program Areas (Source: https://www.data.boem.gov/Main/Mapping.aspx, accessed 12th July 2019.)

Literature cited

Booth, C.G., Oedekoven, C.S., Gillespie, D., Macaulay, J., Plunkett, R, Joy, R., Harris, D., Wood, J., Marques, T. A., Marshall, L., Verfuss, U.K., Tyack, P. Johnson, M., & Thomas, L. 2017. Assessing the Viability of Density Estimation for Cetaceans from Passive Acoustic Fixed Sensors throughout the Life Cycle of an Offshore E&P Field Development. Report number: SMRUC-OGP-2017-001. Available from https://gisserver.intertek.com/JIP/DMS/ProjectReports/Cat4/Other/Booth2017_CetaceansandPAM.pdf

Borchers, D.L., S.T. Buckland and W. Zucchini. 2002. Estimating Animal Abundance: Closed Populations. Springer-Verlag.

Borchers, D.L., B.C. Stevenson, D. Kidney, L. Thomas, T.A. Marques. 2015. A unifying model for capture-recapture and distance sampling surveys of wildlife populations. 2015. Journal of the American Statistical Association 110: 195-204.

Buckland, S.T., D.R. Anderson, K.P. Burnham, J.L. Laake, D.L. Borchers & L. Thomas. 2001. Introduction to Distance Sampling. Oxford University Press.

Carlén, I., L. Thomas, J. Carlström, M. Amundin, J. Teilmann, N. Tregenz, J. Tougaard, J.C. Koblitz, S. Sveegaard, D. Wennerberg, O. Loisa, M. Dähne, K. Brundiers, M. Kosecka, L.A. Kyhne, C.T. Ljungqvist, Pawliczka, I., R. Koza, B. Arciszewski, A. Galatius, M. Jabbusch, J. Laaksonlaita, J. Niemi, S. Lyytinen, A. Gallus, H. Benke, P. Blankett, K.E. Skóra, A. Acevedo-Gutiérrez. 2018. Basin-scale description of the spatial and seasonal distribution of harbour porpoises in the Baltic Sea provides basis for effective conservation actions. Biological Conservation 226: 42-53.

Frasier K. E., A. Solsana Berga, L. Stokes, J.A. Hildebrand. In press. Impacts of the Deepwater Horizon Oil Spill on Marine Mammals and SeaTurtles In S. A. Murawski et al. (Eds.), Deep Oil Spills: Facts, Fate and Effects (pp. 441-472). Cham, Switzerland: Springer

Harris, D., L. Thomas, H. Klinck and D.K. Mellinger. 2019. A framework for cetacean density estimation using slow-moving autonomous ocean vehicles. ONR Annual Report Award number N00014-15-1-2142.

Helble, T.A., G.L. D'Spain, G.S. Campbell and J.A. Hildebrand. 2013. Calibrating passive acoustic monitoring: correcting humpback whale call detections for site-specific and time-dependent environmental characteristics. Journal of the Acoustical Society of America 143: EL400-406.

Johnson, M.E., Moore, L.M., and Ylvisaker, D. (1990). Minimax and maximin distance designs. Journal of Statistical Planning and Inference 26, 131-148.

Latusek-Nabholz, J.N., A.D. Whitt, D. Fertl, D.R. Gallien, A.A. Khan, and N. Sidorovskaia. 2017. Literature Synthesis on Passive Acoustic Monitoring Projects and Sound Sources in the Gulf of Mexico. U.S. Department. of the Interior, Bureau of Ocean Energy Management, Sterling, Virginia. OCS Study BOEM 2017-xxx. 100 pp.

Lavrakas, P.J. 2008. Rotating Panel Designs. In Lavrakas, P. J. Encyclopedia of survey research methods. Sage Publications. doi: 10.4135/9781412963947

Marques, T.A, L. Thomas, S.W. Martin, D.K. Mellinger, J.A. Ward, D.J. Moretti, D. Harris and P.L. Tyack. 2013. Estimating animal population density using passive acoustics. Biological Reviews 88: 287-309.

Marques, T.A., D. Harris and L. Thomas. 2017. Survey design considerations for passive acoustic monitoring of the Gulf of Mexico. Unpublished report dated 30 May 2017.

Norvell, Russ & Howe, Frank & R. Parrish, Jimmie. (2009). A Seven-Year Comparison of Relative-Abundance and Distance-Sampling Methods. The Auk. 120. 1013-1028.

Širović, A., H.R. Bassett, S.C. Johnson, S.M. Wiggins and J.A. Hildebrand 2013. Byrde's whale calls recorded in the Gulf of Mexico. Marine Mammal Science 30: 399-401.

Stevens DL, Olsen AR. 2004. Spatially balanced sampling of natural resources. Journal of the American Statistical Association 99: 262-278.

Stevenson, B. C., D.L. Borchers, R. Altwegg, R.J. Swift, D.M. Gillespie, and G.J. Measey 2015. A general framework for animal density estimation from acoustic detections across a fixed microphone array. Methods in Ecology and Evolution 6, 38–48.

Thompson, S.K. 2012. Sampling (3rd edition). Wiley.

Thomas, L., K.P. Burnham and S.T Buckland. 2004. Temporal inferences from distance sampling surveys. Chapter 5 in Buckland, S.T., D.R. Anderson, K.P. Burnham, J.L. Laake, D.L. Borchers & L. Thomas (Eds.), Advanced Distance Sampling. Oxford University Press.