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Final Report: Integrating Visual and Acoustic Data on Cetacean Abundance and Habitat in the Deep Water Gulf of Mexico

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Executive Summary:

The goal of this project is to build integrated habitat models for Gulf of Mexico marine mammals using visual survey data, and passive acoustic monitoring data. Effective marine mammal population management requires the ability to predict species distributions in space and time. Primary marine mammal population assessment methods include visual surveys which provide good spatial coverage, but limited temporal resolution, and passive acoustic monitoring, which produces good temporal resolution with limited spatial coverage. We explore methods for using both datasets in tandem to train and test habitat models capable of robust spatial and temporal predictive power. Neural networks are proposed as a promising strategy for this type of combined learning problem, and results are presented for seven marine mammal groups including sperm whales, beaked whales and delphinids. The final models and associated information will be made available in a publically accessible online format, for use in management and decision making applications.

Introduction

Conservation and management of cetacean populations requires an understanding of temporal and spatial trends in abundance to predict population responses, quantify trends and mitigate negative impacts (Best et al., 2012; Redfern et al., 2006). The deep water Gulf of Mexico (GoMx) provides habitat for a diverse array of pelagic cetaceans including sperm whales, beaked whales, *Kogia* and a variety of delphinids. These species, which live beyond the continental shelf, are thought to represent the majority of GoMx cetaceans in terms of total numbers (R. W. Davis et al., 2002; Fulling, Mullin, & Hubard, 2003) however the temporal trends and spatial distributions of these populations are poorly understood due to the many challenges of offshore marine mammal surveys.

Shipboard and aerial line-transect surveys are the standard method for estimating abundance and describing the distributions of cetacean populations (Barlow & Forney, 2007; R. Davis et al., 1998; Fulling et al., 2003; K. Mullin & Fulling, 2003, 2004; K. Mullin & Hoggard, 2000). This method relies on sightings at the sea surface. Visual surveys provide broad spatial coverage of the Gulf region at a snapshot in time. Some temporal coverage can be obtained if multiple surveys are combined over many years. However, visual methods are resource intensive, requiring extensive vessel/aircraft and personnel time. They also rely on fair weather conditions, therefore most visual survey effort in the GoMx has occurred in summer months, with least survey effort occurring in winter months (Best et al., 2012; Maze-Foley & Mullin, 2007; K. D. Mullin, 2007).

Static passive acoustic monitoring (PAM) provides a complimentary modality for cetacean monitoring; this approach employs acoustic sensors at fixed sites but provides a nearly continuous record of animal presence at monitored locations. This method relies on underwater detection of species-specific vocalizations. Passive acoustic monitoring data has been collected in GoMx since 2010 using fixed seafloor sensors. The time series from acoustic monitoring sites provide excellent temporal coverage, operating continuously regardless of weather conditions or time of day. However spatial coverage is limited, because sensor locations are fixed and detection ranges are restricted by the acoustic characteristics of the vocalizations monitored.

Visual survey and PAM datasets have been used independently to predict marine mammal distributions across space and time under varying oceanographic conditions, however the limitations of each survey modality respectively result in an incomplete picture of habitat use by marine mammals. We describe a pilot study examining the feasibility of combining visual and acoustic data into joint habitat models capable of leveraging both the spatial coverage of visual survey data and the temporal coverage of static PAM data collected in the Gulf of Mexico. Joint habitat models were developed for seven species or genera.

Methods

Visual Survey

Visual survey data were collected during five cruises conducted by the National Oceanographic and Atmospheric Administration Southeast Fisheries Science Center (NOAA SEFSC) aboard the R/V Gordon Gunter in 2003, 2004, 2009, 2012, and 2014 (Figure 1). These cruises were designed to survey the deep water GOM, therefore the survey area was delimited by the 200m bathymetric contour to the north, west, and east, and by the limit of the US EEZ to the south. Cruises conducted in 2012 and 2014 were limited to the Eastern GOM. Cruise data from 2009 was used only for model for testing, while other years were used for training. Pre-2003 visual survey data is available but was not used due to lack of HYCOM environmental parameter estimates for earlier years.

Visual survey data were re-coded as presence or absence of each species along 10km segments of on-effort transects. Some transect segments were shorter than 10km, and this was accounted for by computing an area A surveyed as

$$A = 2wL$$

where L is the transect segment length in km, and w is the truncation distance in kilometers, calculated as the distance from the transect line within which 95% of the species of interest occurred (Laake, Borchers, Thomas, Miller, & Bishop, 2015). Survey effort speed was >= 10 knots.

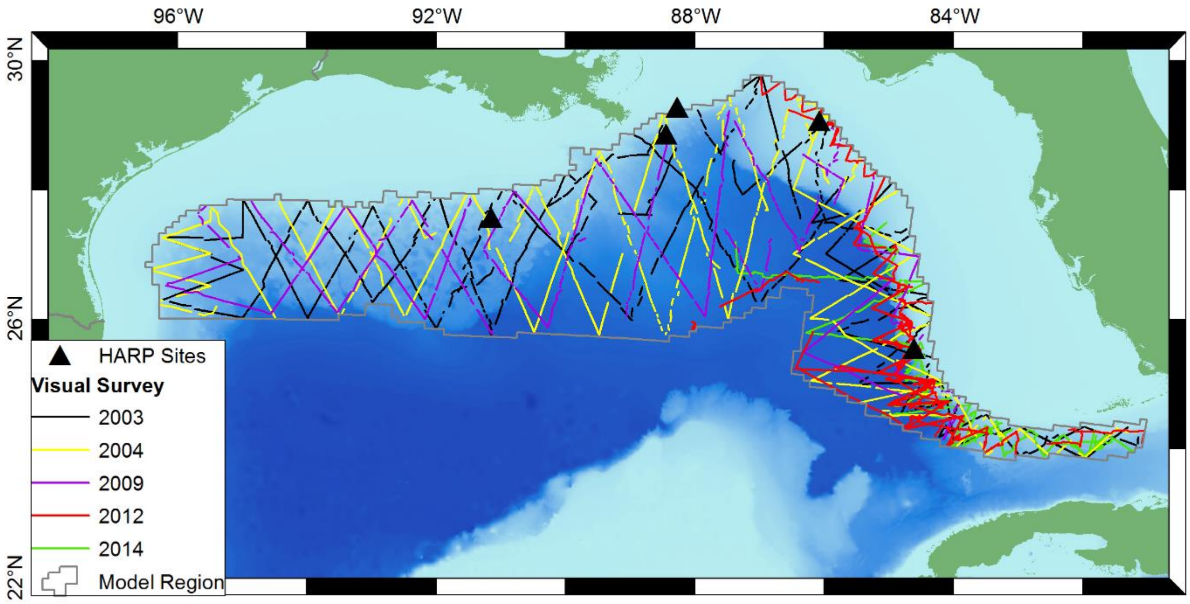

Figure 1. Map of visual and passive acoustic survey data locations used in this study.

Passive Acoustic Monitoring

Passive acoustic monitoring data were collected from five sites in the GoMx between 2011 and 2013 (Figures 1 & 2). Three deep slope sites were used for deep-diving species including sperm whales, beaked whales and *Kogia*. An additional two shelf sites were used for delphinid species. Data from 2011-2012 was used for model training, with 2013 data held back for testing. Echolocation clicks were detected as and manually reviewed by analysts to ensure low false positive and misclassification rates (J. A. Hildebrand et al., submitted).

Encounter data was recoded as presence-absence in one day bins. Acoustic area surveyed was estimated as:

$$A = \pi \cdot w^2$$

Truncation distances were estimated as range within which 95% of detections were expected to occur based on species-specific detection range simulations (Frasier et al., 2016; J. Hildebrand et al., 2015; J. A. Hildebrand et al., submitted).

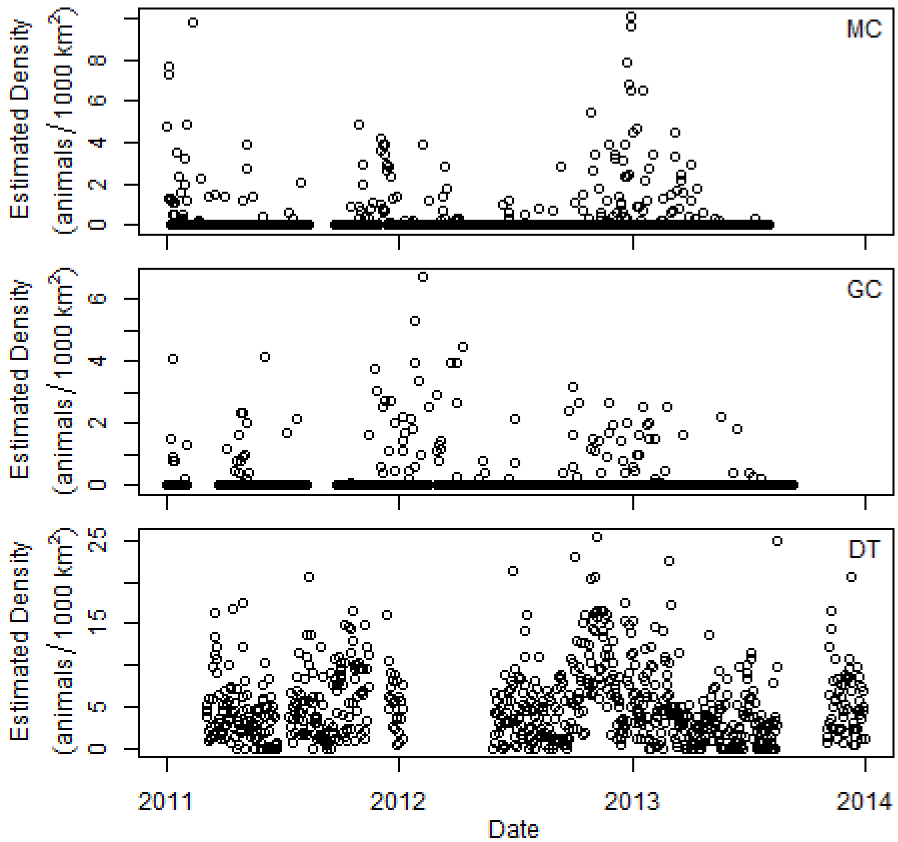

Figure 1. Cuvier's beaked whale density at HARP sites from 2011 to 2014 estimated from passive acoustic monitoring data.

Environmental Parameters

Environmental data were primarily accessed through the Marine Geospatial Ecology Toolkit (MGET; Roberts, Best, Dunn, Treml, & Halpin, 2010) in ArcGIS. Covariates examined included sea surface height (SSH), sea surface temperature (SST), chlorophyll A, distance to nearest eddy, distance to nearest front, mixed layer depth, upwelling speed, salinity, and surface current magnitude (Table 1).

Habitat Modeling

Habitat models were produced for seven genera or species including sperm whale (*Physeter microcephalus*), Cuvier's beaked whale (*Ziphius cavirostris*) Gervais' beaked whale (*Mesoplodon europaeus*), Risso's dolphin (*Grampus grisues*), pygmy/dwarf sperm whale (*Kogia* spp.), pelagic stenellid dolphins (*Stenella* spp.), and pilot whales (*Globicephala* spp.). Species selection and grouping was based on the availability of both visually and acoustically distinctive features. Sperm whale, Cuvier's and Gervais' beaked whale and Risso's dolphin are distinguishable both visually based on size, markings and body shape and acoustically based on characteristic features of their echolocation clicks. *Kogia* species are not visually distinguishable during visual surveys, therefore they were modeled together. Similarly, short and long-finned pilot whales are difficult to distinguish visually in the field. Long-finned pilot whales have not been conclusively identified in the GOM, therefore primarily short-finned pilot whales are expected. Pilot whale echolocation clicks have been tentatively identified in the in acoustic record (Frasier et al. 2017). Pelagic stenellid dolphins (genus *Stenella*) are the most common pelagic delphinids in the GoMx. This group consists of five species species with similar click types which were modeled together including spinner (*Stenella longriostris longirostris*), Clymene (*Stenella clymene*), pantropical spotted (*Stenella attenuata*), Atlantic spotted (*Stenella frontalis*), and striped dolphins (*Stenella coeruleoalba*).

Model Implementation

A variety of modeling frameworks were evaluated for suitability, including GEE GLM, GAM, GAMM, and neural networks. After extensive evaluation, we were most satisfied with the few assumptions and overall simplicity of neural networks for this case.

Neural networks were implemented using *avNNet* in the *caret* package (Kuhn et al., 2017), which allows multiple iterations to be run within a multi-fold framework and can be used to compute an average network across many training iterations. Critically, this package also implements case weights, such that some training data points can be given more weight than others. This was a key part of integrating the two datasets. Each observation O_i, for *i* in the set of observations *N*, was weighted in joint models according to spatial and temporal coverage using the following formula:

$$W(Oi) \ = \ \frac{A(Oi) \ \cdot \ D(Oi)}{\frac{1}{n}\sum_{i=1}^{n} mean(A(Oi) \cdot \ D(Oi))}$$

where *D* is the duration of the observation period, and *n* is the number of observations in *N*.

Further, zeros in the visual data were down-weighted to account for the probability of observing animals at the sea surface (G_0) as

$$W_{G0}(Oi) = \begin{cases} W(Oi) \text{ if } \ Oi > \ 0 \\ G_0 W(Oi) \text{ if } \ Oi = \ 0 \end{cases}$$

Species-specific G_0 estimate were calculated from double-blind visual surveys (Palka, 2006).

Bagging was used to reduce network overtraining, and tested hidden layer sizes ranging from 2-14 nodes. A single, fully-connected hidden layer was used. We used a node weight decay of 1e4, with maximum conditional likelihood as the cost function, and randomly initialized node weights from -0.7 to 0.7. Models were compared using weighted cross-entropy to compare predicted and observed presence/absence in the test data. The hidden layer size that minimized the cross entropy on the test dataset after 50 training iterations was selected as the best network configuration.

Results

Environmental Variability

The range of oceanographic variables observed differed between the visual and PAM survey methods (Table 1). Visual survey track lines across the GoMx surveyed within loop current-associated features and eddies more often than PAM sensors, and therefore traversed a wider range of sea surface heights and current magnitudes. By monitoring year-round, PAM sensors observed a wider range of sea surface temperatures, mixed layer depths, and chlorophyll A concentrations. Similar ranges of salinity and vertical transport velocity were observed by the two methods.

Table 1. Comparison of environmental variability observed in the visual survey and PAM datasets.

Oceanographic Variable	Survey Method	Mean [5^{th}, 95^{th} percentile]	Data source
Sea Surface Temperature (^{0} C)	Visual Acoustic	28.39 [23.22, 30.41] 25.57 [20.46, 30.17]	GHRSST Level 4 (JPL MUR MEaSUREs Project, 2015)
Sea Surface Height Anomaly (m)	Visual Acoustic	0.06 [-0.20, 0.44] 0.06 [-0.08, 0.20]	JPL (Zlotnicki, Qu, & Willis, 2016)
Salinity (PSU)	Visual Acoustic	35.3 [33.8, 36.1] 34.9 [33.1, 36.2]	HYCOM (Chassignet et al., 2009)
Mixed Layer Depth (m)	Visual Acoustic	10.9 [2.2, 29.2] 21.2 [2.4, 59.3]	HYCOM (Chassignet et al., 2009)
Distance to Nearest Eddy (km)	Visual Acoustic	70.9 [0.0, 185.2] 136.9 [37.1, 284.8]	Derived from JPL (Zlotnicki et al., 2016)
Surface Current Magnitude	Visual Acoustic	0.54 [0.10, 1.41] 0.29 [0.07, 0.63]	HYCOM (Chassignet et al., 2009)
Chlorophyll A	Visual Acoustic	0.196 [0.062, 0.525] 0.678 [0.102, 3.223]	NASA OceanColor group (NASA Goddard Space Flight Center, 2014)
Vertical water velocity at 50m depth (m/sec)	Visual Acoustic	-8.84e-06 [-3.45e-4, 3.17e-4] -1.89e-05 [-3.43e-4, 2.67e-4]	HYCOM (Chassignet et al., 2009)

Data Weighting

Weight ratios between visual and acoustic observations varied by species according to method and species-specific detectability estimates (Table 2). In general, acoustic observations received more weight than visual observations because each data point represented more observation time. An exception was *Kogia* spp. which has a short acoustic detection range, and therefore positive visual observations were weighted more heavily than acoustic observations.

Table 2. Relative observation weighting parameters for acoustic and visual survey methods.

Species	Survey Method	Truncation Distance (km)	Observation Duration (hrs)	Relative Weight (Acoustic:Visual)	G_0
Cuvier's beaked whale	Visual Acoustic	5.4 1.3	0.54 24	2.18:1	0.29 1
Gervais' beaked whale	Visual Acoustic	2.2 1.0	0.54 24	3.17:1	0.29 1
Sperm whale	Visual Acoustic	6.8 7.0	0.54 24	55:1	0.52 1
Kogia spp.	Visual Acoustic	4.0 0.7	0.54 24	0.86:1	0.42 1
Stenella spp.	Visual Acoustic	5.1 1.3	0.54 24	2.3:1	0.67 1
Risso's dolphin	Visual Acoustic	5.3 1.9	0.54 24	4.5:1	0.81 1
Pilot whale	Visual Acoustic	6.5 1.9	0.54 24	3.9:1	0.67 1

Model Comparisons

Habitat models were trained and tested on the acoustic dataset (acoustic-only models), the visual dataset (visual-only models), and on the combined acoustic and visual datasets (joint models). Detailed results for each genus and species modeled are provided at https://goo.gl/MY65na along with open source code used to generate the results. Monthly distribution maps are being prepared for hosting on CetMap in early 2018.

Model predictions differed significantly depending on the method used. Visual-only models typically found weaker relationships between environmental factors and encounter rates than acoustic-only models. Visual models were prone to overfitting, due to low sighting rates. This effect was mitigated in part by developing weighting strategies to account for zero-inflation associated with missing animals not available at the sea surface. Visual-only models were not able to accurately predict encounter-rates at passive acoustic monitoring sites, and showed limited ability to predict spatial observations in the visual test set.

Acoustic-only models were effective at predicting encounter rates in the passive acoustic test set, and spatial distributions observed in the visual test data, but they tended to overemphasize the influence of conditions observed at specific sites. This effect would likely be mitigated by the use of a larger number of monitoring locations.

Joint models were a tempered combination of the acoustic and visual-only models, however joint predictions did not merely reflect the average of the two methods. Rather, new patterns were identified by running the learning algorithm on the combined datasets. Joint models were often effective at spatial and temporal prediction, however more data is needed to evaluate predictions in non-summer months.

Predictive power of the various environmental factors varied by species (Table 3). Sea surface temperature and sea surface height were often strong predictors, while upwelling and current magnitude were typically weak. A range of network complexities were compared, however network predictions were not sensitive to small changes in hidden layer size.

Table 3. Comparison of relative environmental variable influence on predicted encounters by species in joint habitat models.

Environmental Driver	Cuvier's beaked whale	*Kogia* spp.	Sperm whale
Sea surface temperature	13.4	10.3	12.9
Sea surface height	14.1	19.7	23.6
Chlorophyll A	21.9	19.0	13.2
Mixed layer depth	8.5	8.4	12.0
Salinity	14.2	12.6	16.4
Current magnitude	7.9	8.3	6.5
Upwelling	8.8	10.7	7.4
Eddy Distance	1.2	11.0	8.0
TOTAL	100	100	100

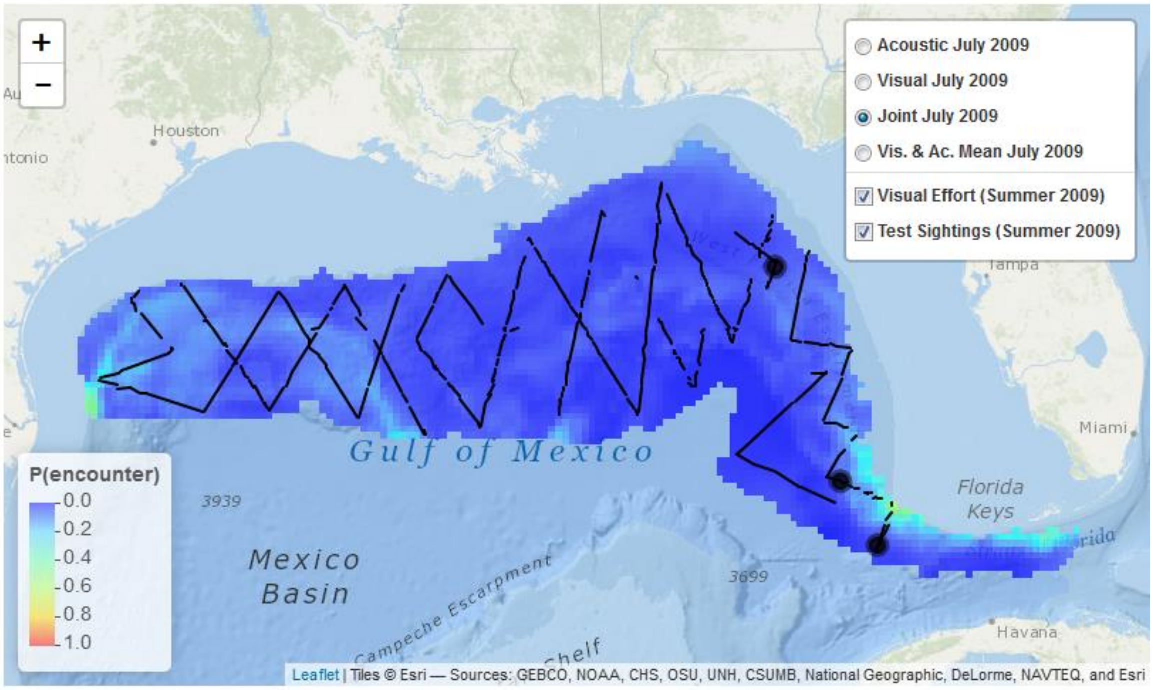

Figure 3. Summer 2009 Cuvier's beaked whale distribution predicted by the joint habitat model (top) predicts the observed spatial distribution from the visual test data (black dots).

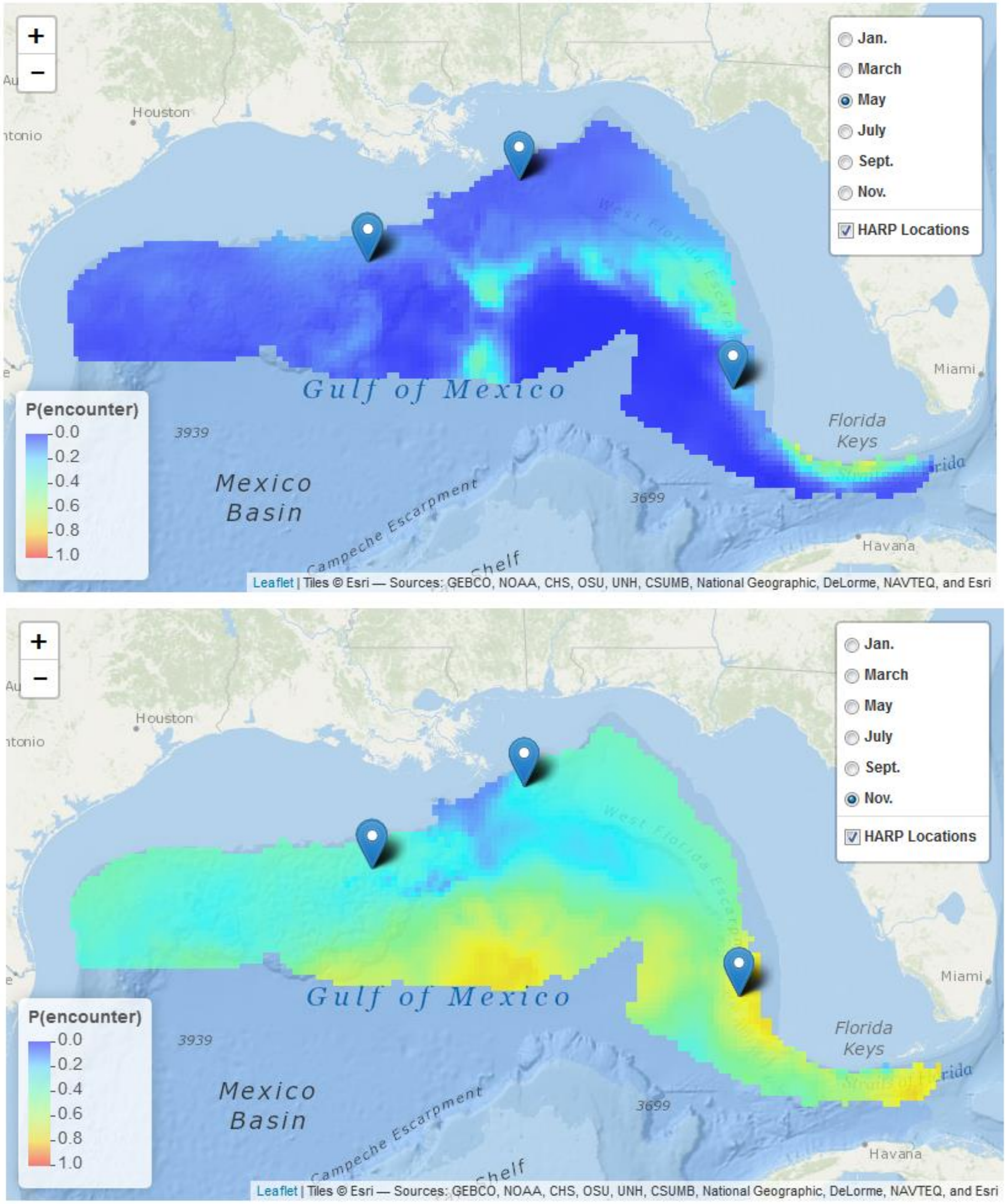

Figure 4. Predicted mean distribution of Cuvier's beaked whale in May (top) and November (bottom) from joint model predictions on mean climatological conditions between 2003 and 2015. Blue location markers indicate deep HARP monitoring sites.

Discussion

Combining passive acoustic and visual marine mammal survey data can improve habitat model predictions. However, combining these distinct data types requires a thorough understanding of the relative strength of the observations, treatment of zero-inflation, and restricting explored environmental drivers to conditions that are broadly variable within both datasets. Further, non-linear relationships and complex interactions in these datasets make many traditional model frameworks unsuitable. We determined that neural networks are a promising solution for learning from mixed datasets due to their flexibility, minimal heuristics, and ability to learn unspecified complex interactions between drivers. Historically neural networks have been thought of as “black boxes”, however straightforward methods now exist for interpreting environmental variable importance and the interactions between variables within networks.

Although the PAM sensor locations were fixed, approximately half of the oceanographic covariates were more varied for the PAM dataset than the visual dataset, primarily due to the year-round sampling capabilities of PAM. The GoMx has an extended storm season (hurricanes), which produces different conditions in winter and spring than those observed during the typical summer survey months. Differences included a deeper mixed layer and colder temperatures.

Future work may include adding aerial survey data to include predictions over continental shelf regions, and future ship-board survey data planned for winter months could be used to test un-validated predictions outside of summer months. The visual survey dataset could be expanded to include pre-2003 data by using climatologies for variables including salinity, MLD. Roberts et al. (2016) indicated that climatologies had better predictive power for visual-only models, however the use of these environmental averages may obscure fine-scale relationships and require an assumption of inter-annual consistency despite a changing climate. The addition of acoustic monitoring sites in the western GoMx and beyond the continental slope would likely improve model predictions and allow the use of additional relevant predictors including bottom depth and current direction.

Conclusion

Visual surveys and PAM are complementary marine mammal observation modalities with differing spatial and temporal coverage. Habitat models were trained using both datatypes to improve forecasting and to estimate encounter probabilities in under-surveyed regions and seasons. Spatiotemporal marine mammal distribution estimates are critical for designing management frameworks that support marine mammal population recovery by minimizing overlap between human activities and critical habitat.

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