Density Model for Atlantic Spotted Dolphin (*Stenella frontalis*) for the U.S. East Coast: Supplementary Report

Model Version 9.1

Duke University Marine Geospatial Ecology Laboratory[*]

2023-05-27

Citation

When citing our methodology or results generally, please cite Roberts et al. (2016, 2023). The complete references appear at the end of this document. We are preparing a new article for a peer-reviewed journal that will eventually replace those. Until that is published, those are the best general citations.

When citing this model specifically, please use this reference:

Roberts JJ, Yack TM, Cañadas A, Fujioka E, Halpin PN, Barco SG, Boisseau O, Chavez-Rosales S, Cole TVN, Cotter MP, Cummings EW, Davis GE, DiGiovanni Jr. RA, Garrison LP, Gowan TA, Jackson KA, Kenney RD, Khan CB, Lockhart GG, Lomac-MacNair KS, McAlarney RJ, McLellan WA, Mullin KD, Nowacek DP, O'Brien O, Pabst DA, Palka DL, Quintana-Rizzo E, Redfern JV, Rickard ME, White M, Whitt AD, Zoidis AM (2022) Density Model for Atlantic Spotted Dolphin (*Stenella frontalis*) for the U.S. East Coast, Version 9.1, 2023-05-27, and Supplementary Report. Marine Geospatial Ecology Laboratory, Duke University, Durham, North Carolina.

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Model Version History

Version	Date	Description
1	2014-05-14	Initial version.
2	2014-09-02	Added surveys: NJ-DEP, Virginia Aquarium, NARWSS 2013, UNCW 2013. Extended study area up Scotian Shelf. Added SEAPODYM predictors. Switched to mgcv estimation of Tweedie p parameter (family=tw()).
3	2014-10-17	Adjusted g(0) estimates based on feedback from September 2014 review. Adjusted proxy species used in certain detection functions to be consistent with other dolphin species. Updated distance to eddy predictors using Chelton et al.'s 2014 database. Removed distance to eddy and wind speed predictors from on shelf model. Fixed missing pixels in several climatological predictors, which led to not all segments being utilized.
4	2014-11-13	Reconfigured detection hierarchy and adjusted NARWSS detection functions based on additional information from Tim Cole. Updated documentation.
5	2014-11-19	Removed CumVGPM180 predictor and refitted models. Updated documentation.

[*]For questions or to offer feedback please contact Jason Roberts (jason.roberts@duke.edu) and Tina Yack (tina.yack@duke.edu)

(continued)

Version	Date	Description
6	2014-12-05	Fixed bug that applied the wrong detection function to segments NE_narwss_1999_widgeon_hapo dataset. Refitted model. Updated documentation.
7	2015-01-24	Forced abundance to zero in the vicinity of New York-New Jersey Harbor. We found no documentation that Atlantic spotted dolphins occur here, but our model predicts some abundance. We believe this prediction is in error and are manually correcting it.
7.1	2015-03-06	Updated the documentation. No changes to the model.
7.2	2015-05-14	Updated calculation of CVs. Switched density rasters to logarithmic breaks. No changes to the model.
7.3	2015-09-03	Updated the documentation. No changes to the model. Model files released as supplementary information to Roberts et al. (2016).
8	2018-04-14	Began update to Roberts et al. (2015) model. Introduced new surveys from AMAPPS, NARWSS, UNCW, VAMSC, and the SEUS NARW teams. Updated modeling methodology. Refitted detection functions and spatial models from scratch using new and reprocessed covariates. Model released as part of a scheduled update to the U.S. Navy Marine Species Density Database (NMSDD).
9	2022-06-20	This model is a major update over the prior version, with substantial additional data, improved statistical methods, and an increased spatial resolution. It was released as part of the final delivery of the U.S. Navy Marine Species Density Database (NMSDD) for the Atlantic Fleet Testing and Training (AFTT) Phase IV Environmental Impact Statement. Several new collaborators joined and contributed survey data: New York State Department of Environmental Conservation, TetraTech, HDR, and Marine Conservation Research. We incorporated additional surveys from all continuing and new collaborators through the end of 2020. (Because some environmental covariates were only available through 2019, certain models only extend through 2019.) We increased the spatial resolution to 5 km and, at NOAA's request, we extended the model further inshore from New York through Maine. We reformulated and refitted all detection functions and spatial models. We updated all enviromental covariates to newer products, when available, and added several covariates to the set of candidates. For models that incorporated dynamic covariates, we estimated model uncertainty using a new method that accounts for both model parameter error and temporal variability.
9.1	2023-05-27	Completed the supplementary report documenting the details of this model. The model itself was not changed.

1 Survey Data

We built this model from data collected between 1998-2020 (Table 1, Figure 1). We excluded surveys that did not target small cetaceans or were otherwise problematic for modeling them. Because of species identification problems prior to 1998 (see Section 5 for details), we excluded surveys prior to 1998. We restricted the model to aerial survey transects with sea states of Beaufort 4 or less (for a few surveys we used Beaufort 3 or less) and shipboard transects with Beaufort 5 or less (for a few we used Beaufort 4 or less). We also excluded transects with poor weather or visibility for surveys that reported those conditions.

Table 1: Survey effort and observations considered for this model. Effort is tallied as the cumulative length of on-effort transects. Observations are the number of groups and individuals encountered while on effort. Off effort observations and those lacking an estimate of group size or distance to the group were excluded.

			Effort	Observations		
Institution	Program	Period	1000s km	Groups	Individuals	Mean Group Size
Aerial Surveys						
HDR	Navy Norfolk Canyon	2018-2019	10	19	1,644	86.5
NEFSC	AMAPPS	2010-2019	83	0	0	
NEFSC	NARWSS	2003-2016	380	0	0	
NEFSC	Pre-AMAPPS	1999-2008	45	1	2	2.0
SEFSC	AMAPPS	2010-2020	112	204	3,543	17.4
SEFSC	MATS	2002-2005	27	104	1,828	17.6
UNCW	MidA Bottlenose	2002-2002	15	1	6	6.0
UNCW	Navy Cape Hatteras	2011-2017	34	49	2,596	53.0
UNCW	Navy Jacksonville	2009-2017	92	331	6,004	18.1
UNCW	Navy Norfolk Canyon	2015-2017	14	34	1,686	49.6
UNCW	Navy Onslow Bay	2007-2011	49	63	1,505	23.9
UNCW	SEUS NARW EWS	2005-2008	106	4	57	14.2
VAMSC	MD DNR WEA	2013-2015	15	1	45	45.0
VAMSC	Navy VACAPES	2016-2017	18	2	155	77.5
VAMSC	VA CZM WEA	2012-2015	19	2	64	32.0
		Total	**1,020**	**815**	**19,135**	**23.5**
Shipboard Surveys						
MCR	SOTW Visual	2012-2019	9	8	72	9.0
NEFSC	AMAPPS	2011-2016	15	53	1,449	27.3
NEFSC	Pre-AMAPPS	1998-2007	13	13	394	30.3
NJDEP	NJEBS	2008-2009	14	0	0	
SEFSC	AMAPPS	2011-2016	16	84	3,040	36.2
SEFSC	Pre-AMAPPS	1998-2006	30	364	8,579	23.6
		Total	**96**	**522**	**13,534**	**25.9**
		Grand Total	**1,115**	**1,337**	**32,669**	**24.4**

Table 2: Institutions that contributed surveys used in this model.

Institution	Full Name
HDR	HDR, Inc.
MCR	Marine Conservation Research
NEFSC	NOAA Northeast Fisheries Science Center
NJDEP	New Jersey Department of Environmental Protection
SEFSC	NOAA Southeast Fisheries Science Center
UNCW	University of North Carolina Wilmington
VAMSC	Virginia Aquarium & Marine Science Center

Table 3: Descriptions and references for survey programs used in this model.

Program	Description	References
AMAPPS	Atlantic Marine Assessment Program for Protected Species	Palka et al. (2017), Palka et al. (2021)
MATS	Mid-Atlantic Tursiops Surveys	
MD DNR WEA	Aerial Surveys of the Maryland Wind Energy Area	Barco et al. (2015)
MidA Bottlenose	Mid-Atlantic Onshore/Offshore Bottlenose Dolphin Surveys	Torres et al. (2005)
NARWSS	North Atlantic Right Whale Sighting Surveys	Cole et al. (2007)
Navy Cape Hatteras	Aerial Surveys of the Navy's Cape Hatteras Study Area	McLellan et al. (2018)
Navy Jacksonville	Aerial Surveys of the Navy's Jacksonville Study Area	Foley et al. (2019)
Navy Norfolk Canyon	Aerial Surveys of the Navy's Norfolk Canyon Study Area	Cotter (2019), McAlarney et al. (2018)
Navy Onslow Bay	Aerial Surveys of the Navy's Onslow Bay Study Area	Read et al. (2014)
Navy VACAPES	Aerial Survey Baseline Monitoring in the Continental Shelf Region of the VACAPES OPAREA	Mallette et al. (2017)
NJEBS	New Jersey Ecological Baseline Study	Geo-Marine, Inc. (2010), Whitt et al. (2015)
Pre-AMAPPS	Pre-AMAPPS Marine Mammal Abundance Surveys	Mullin and Fulling (2003), Garrison et al. (2010), Palka (2006)
SEUS NARW EWS	Southeast U.S. Right Whale Early Warning System Surveys	
SOTW Visual	R/V Song of the Whale Visual Surveys	Ryan et al. (2013)
VA CZM WEA	Virginia CZM Wind Energy Area Surveys	Mallette et al. (2014), Mallette et al. (2015)

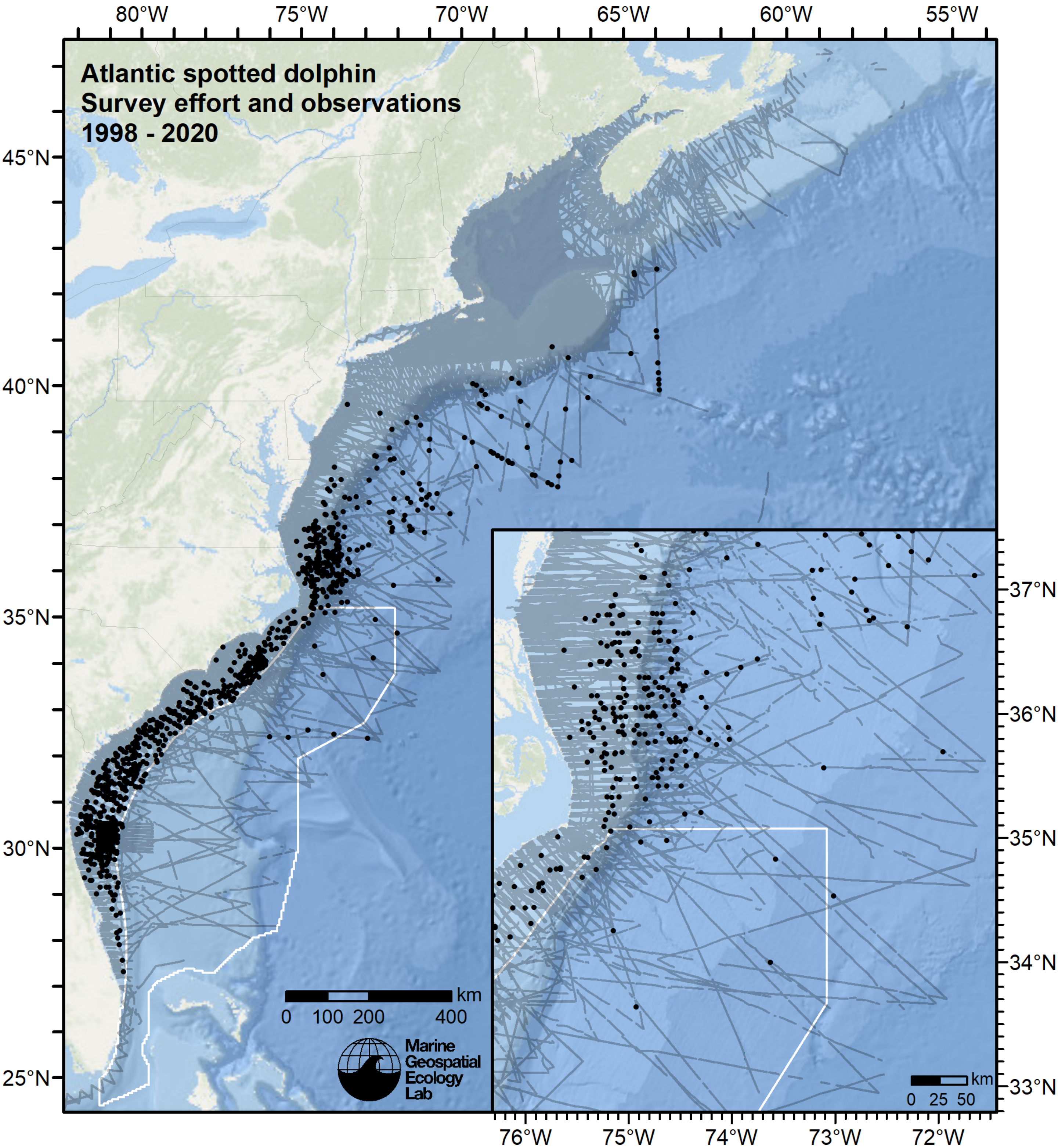


Figure 1: Survey effort and Atlantic spotted dolphin observations available for density modeling, after detection functions were applied, and excluded segments and truncated observations were removed.

2 Classification of Ambiguous Sightings

Observers occasionally experience difficulty identifying species, due to poor sighting conditions or phenotypic similarities between the possible choices. For example, observers may not always be able to distinguish fin whales from sei whales due their similiar size and shape. When this happens, observers will report an ambiguous identification, such as "fin or sei whale". In our density models, we handled ambiguous identifications in three ways:

1. For sightings with very generic identifications such as "large whale", we discarded the sightings. These sightings represented a clear minority when compared to those with definitive species identifications, but they are uncounted animals and our density models may therefore underestimate density to some degree.
2. For sightings of certain taxa in which a large majority of identifications were ambiguous (e.g. "unidentified pilot whale") rather than specific (e.g. "short-finned pilot whale" or "long-finned pilot whale"), it was not tractable to model the individual species so we modeled the generic taxon instead.
3. For sightings that reported an ambiguous identification of two species (e.g. "fin or sei whale") that are known to exhibit different habitat preferences or typically occur in different group sizes, and for which we had sufficient number of definitive sightings of both species, we first fitted a predictive model that classified the ambiguous sightings into one species or the other and then included the resulting classified sightings in the density models for each of the two species.

This section describes how we classified the third category of ambiguous sightings reported as "Atlantic spotted or bottlenose dolphin" into one species or the other.

For the predictive model, we used the cforest classifier (Hothorn et al. 2006), an elaboration of the classic random forest classifier (Breiman 2001). First, we trained a binary classifier using the sightings that reported definitive species identifications ("Atlantic spotted dolphin" and "bottlenose dolphin"). To increase the range of sampling of the classification model's covariates, the training data may have included additional surveys not considered for the density model, as well as transects from outside the spatial and temporal extents of the density model. Only on-effort sightings were used. We used the species ID as the response variable and environmental variables as covariates.

We used receiver operating characteristic (ROC) curve analysis to select a threshold for classifying the probabilistic predictions of species identifications made by the model into a binary result of one species or another. For the classification threshold, we selected the value that maximized the Youden index (Perkins and Schisterman 2006). Then, for all sightings reporting the ambiguous identification, we classified each as either one species or the other by processing the covariate values observed for it through the fitted model. We then included the classified sightings in the detection functions and density models. The sightings reported elsewhere in this document incorporate both the definitive sightings and the classified sightings, unless otherwise noted.

2.1 Classification Model

```
MODEL SUMMARY:
==============

Random Forest using Conditional Inference Trees

Number of trees: 100

Response: factor(OriginalScientificName)
Inputs: ClimChl, ClimDistToAEddy, ClimMnkEpi, ClimSST_CMC, ClimTKE, ClimZoo_SEAPODYM, Depth,
DistTo125m, DistTo300m, DistToShore, Slope
Number of observations: 10000

Number of variables tried at each split: 5

Estimated predictor variable importance (conditional = FALSE):

Importance
ClimZoo_SEAPODYM 0.02315
ClimChl 0.02170
DistToShore 0.01957
```

```
Slope 0.01445
ClimMnkEpi 0.01376
ClimTKE 0.01314
ClimSST_CMC 0.01227
ClimDistToAEddy 0.01017
Depth 0.00925
DistTo125m 0.00750
DistTo300m 0.00624

MODEL PERFORMANCE SUMMARY:
==========================

Statistics calculated from the training data.

Area under the ROC curve (auc)           = 0.977
Mean cross-entropy (mxe)                 = NA
Precision-recall break-even point (prbe) = 0.964
Root-mean square error (rmse)            = 0.224

User-specified cutoff = 0.560

Confusion matrix for that cutoff:

                              Actual Tursiops truncatus  Actual Stenella frontalis  Total
Predicted Tursiops truncatus                       8229                        303   8532
Predicted Stenella frontalis                        304                       1164   1468
Total                                              8533                       1467  10000

Model performance statistics for that cutoff:

Accuracy (acc)                                = 0.939
Error rate (err)                              = 0.061
Rate of positive predictions (rpp)            = 0.853
Rate of negative predictions (rnp)            = 0.147

True positive rate (tpr, or sensitivity)      = 0.964
False positive rate (fpr, or fallout)         = 0.207
True negative rate (tnr, or specificity)      = 0.793
False negative rate (fnr, or miss)            = 0.036

Positive prediction value (ppv, or precision) = 0.964
Negative prediction value (npv)               = 0.793
Prediction-conditioned fallout (pcfall)       = 0.036
Prediction-conditioned miss (pcmiss)          = 0.207

Matthews correlation coefficient (mcc)        = 0.758
Odds ratio (odds)                             = 103.988
SAR                                           = 0.713

Cohen's kappa (K)                             = 0.758
```

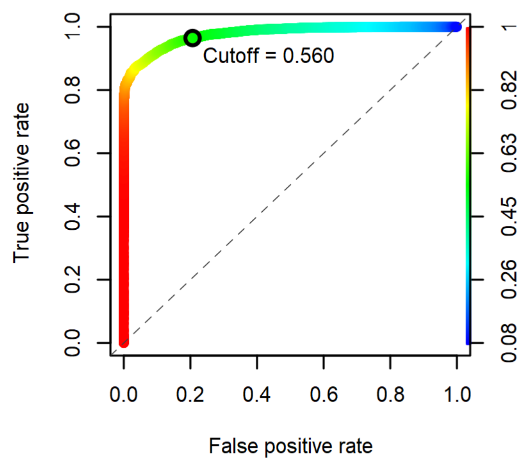
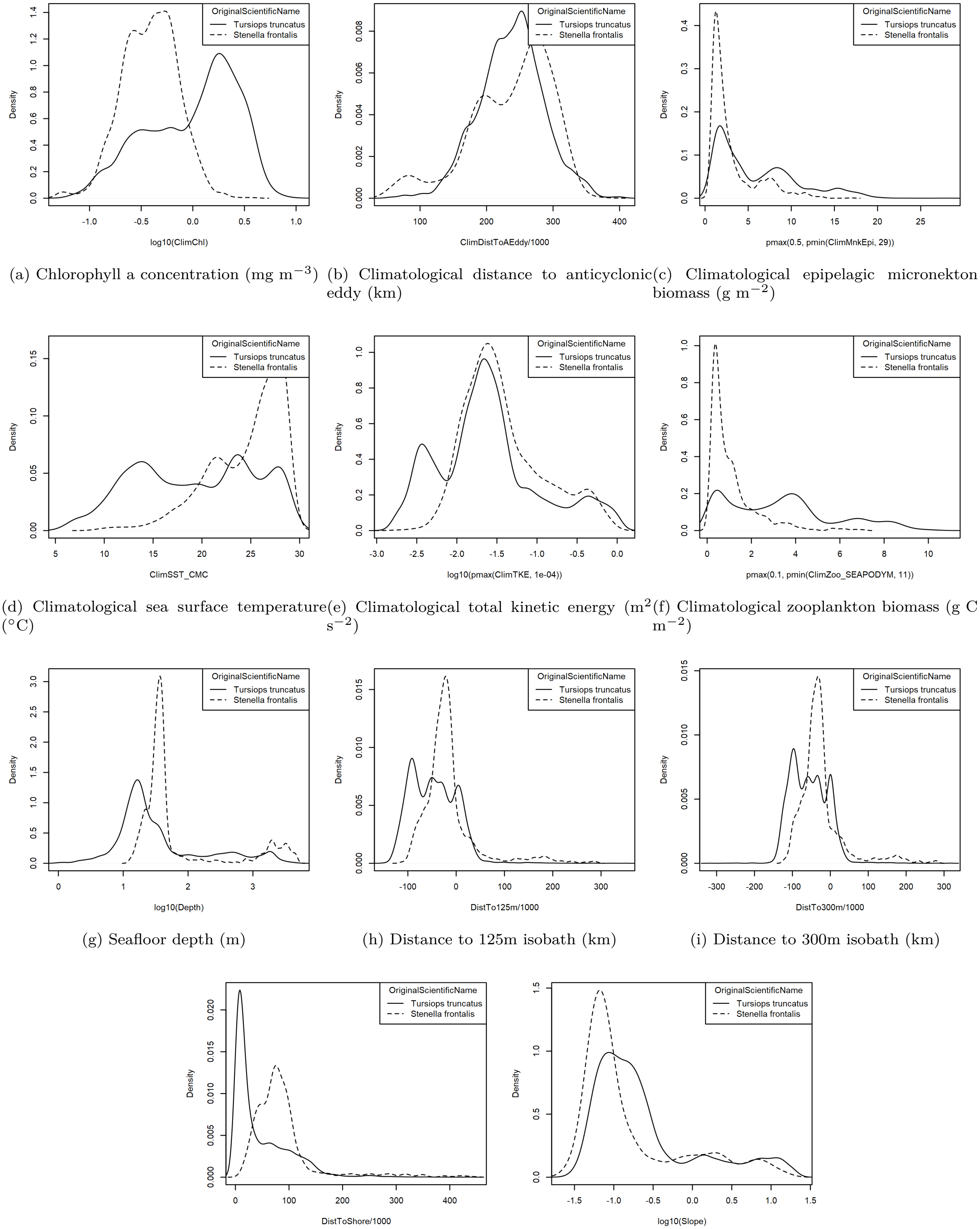


Figure 2: Receiver operating characteristic (ROC) curve summarizing the predictive performance of the ambiguous sighting classification model.

Table 4: Covariates used in the ambiguous sighting classification model.

Covariate	Description
ClimChl	Climatological monthly mean chlorophyll a concentration (mg m^{-3}) from Copernicus GlobColour (Garnesson et al. (2019)), provided by E.U. Copernicus Marine Service (product OCEANCOLOUR_GLO_CHL_L4_REP_OBSERVATIONS_009_082)
ClimDistToAEddy	Climatological monthly mean distance (km) to the edge of the closest anticyclonic mesoscale eddy of any age, derived with MGET (Roberts et al. (2010)) from the Aviso Mesoscale Eddy Trajectories Atlas (META2.0), produced by SSALTO/DUACS and distributed by AVISO+ (https://aviso.altimetry.fr) with support from CNES, in collaboration with Oregon State University with support from NASA, using the method of Schlax and Chelton (2016), based on Chelton et al. (2011)
ClimMnkEpi	Climatological monthly mean micronekton biomass available in the epipelagic zone, expressed as wet weight (g m^{-2}), from SEAPODYM (Lehodey et al. (2008); Lehodey et al. (2015)), provided by E.U. Copernicus Marine Service. doi: 10.48670/moi-00020. Computed as the sum of the SEAPODYM mnkc_epi, mnkc_mumeso, and mnkc_hmlmeso variables.
ClimSST_CMC	Climatological monthly mean sea surface temperature (°C) from GHRSST Level 4 CMC0.2deg and CMC0.1deg (Brasnett (2008); Canada Meteorological Center (2012); Meissner et al. (2016); Canada Meteorological Center (2016))
ClimTKE	Climatological monthly mean total kinetic energy (m^2 s^{-2}) derived from Aviso Ssalto/Duacs global gridded L4 reprocessed geostrophic currents, produced and distributed by E.U. Copernicus Marine Service. doi: 10.48670/moi-00148
ClimZoo_SEAPODYM	Climatological monthly mean zooplankton biomass expressed in carbon (g C m^{-2}) from SEAPODYM (Lehodey et al. (2008); Lehodey et al. (2015)), provided by E.U. Copernicus Marine Service. doi: 10.48670/moi-00020
Depth	Depth (m) of the seafloor, from SRTM30_PLUS (Becker et al. (2009))
DistTo125m	Distance (km) to the 125m isobath, derived from SRTM30_PLUS (Becker et al. (2009))
DistTo300m	Distance (km) to the 300m isobath, derived from SRTM30_PLUS (Becker et al. (2009))
DistToShore	Distance (km) to shore excluding Bermuda and Sable Island, derived from SRTM30_PLUS (Becker et al. (2009))
Slope	Slope (percent rise) of the seafloor, derived from SRTM30_PLUS (Becker et al. (2009))



(a) Chlorophyll a concentration (mg m^{-3})

(b) Climatological distance to anticyclonic eddy (km)

(c) Climatological epipelagic micronekton biomass (g m^{-2})

(d) Climatological sea surface temperature (°C)

(e) Climatological total kinetic energy (m^2 s^{-2})

(f) Climatological zooplankton biomass (g C m^{-2})

(g) Seafloor depth (m)

(h) Distance to 125m isobath (km)

(i) Distance to 300m isobath (km)

(j) Distance to shore (km)

(k) Seafloor slope (percent rise)

Figure 3: Density histograms showing the per-species distribution of each covariate in the ambiguous sighting classification model. When a covariate exhibits a substantially different distribution for each species, it is a good candidate for differentiating the species. Transforms and other treatments are indicated in axis labels. *log10* indicates the covariate was $\log_{10}$ transformed. *pmax* and *pmin* indicate the covariate's minimum and maximum values, respectively, were Winsorized to the values shown. */1000* indicates meters were transformed to kilometers for interpretation convenience.

2.2 Classifications Performed

Table 5: Summary of the definitive sightings used to train the classification model, the ambiguous sightings to which the model was applied, and their resulting classifications. To increase the range of sampling of the classification model's covariates, the training data may have included additional surveys not considered for the density model, as well as transects from outside the spatial and temporal extents of the density model. Only on-effort sightings were used.

		Definitive			Classified	
Institution	Program	S. frontalis	T. truncatus	Ambiguous	S. frontalis	T. truncatus
Aerial Surveys						
HDR	Navy Norfolk Canyon	31	214	0	0	0
NEAq	CNM	2	16	0	0	0
NEAq	MMS-WEA	0	25	0	0	0
NEAq	NLPSC	0	24	0	0	0
NEFSC	AMAPPS	0	112	0	0	0
NEFSC	NARWSS	0	70	0	0	0
NEFSC	Pre-AMAPPS	1	99	0	0	0
NJDEP	NJEBS	0	91	0	0	0
NYS-DEC/TT	NYBWM	0	35	0	0	0
SEFSC	AMAPPS	288	1,865	115	42	73
SEFSC	MATS	100	679	20	8	12
SEFSC	SECAS	10	185	34	7	27
UNCW	MidA Bottlenose	1	348	0	0	0
UNCW	Navy Cape Hatteras	50	297	0	0	0
UNCW	Navy Jacksonville	343	428	0	0	0
UNCW	Navy Norfolk Canyon	37	69	0	0	0
UNCW	Navy Onslow Bay	65	148	0	0	0
UNCW	SEUS NARW EWS	5	1,784	0	0	0
VAMSC	MD DNR WEA	2	556	0	0	0
VAMSC	Navy VACAPES	2	135	0	0	0
VAMSC	VA CZM WEA	3	150	0	0	0
	Total	**940**	**7,330**	**169**	**57**	**112**
Shipboard Surveys						
MCR	SOTW Visual	5	21	0	0	0
NEFSC	AMAPPS	54	272	0	0	0
NEFSC	Pre-AMAPPS	16	177	0	0	0
NJDEP	NJEBS	0	160	0	0	0
SEFSC	AMAPPS	82	158	12	3	9
SEFSC	Pre-AMAPPS	370	415	35	12	23
	Total	**527**	**1,203**	**47**	**15**	**32**
	Grand Total	**1,467**	**8,533**	**216**	**72**	**144**

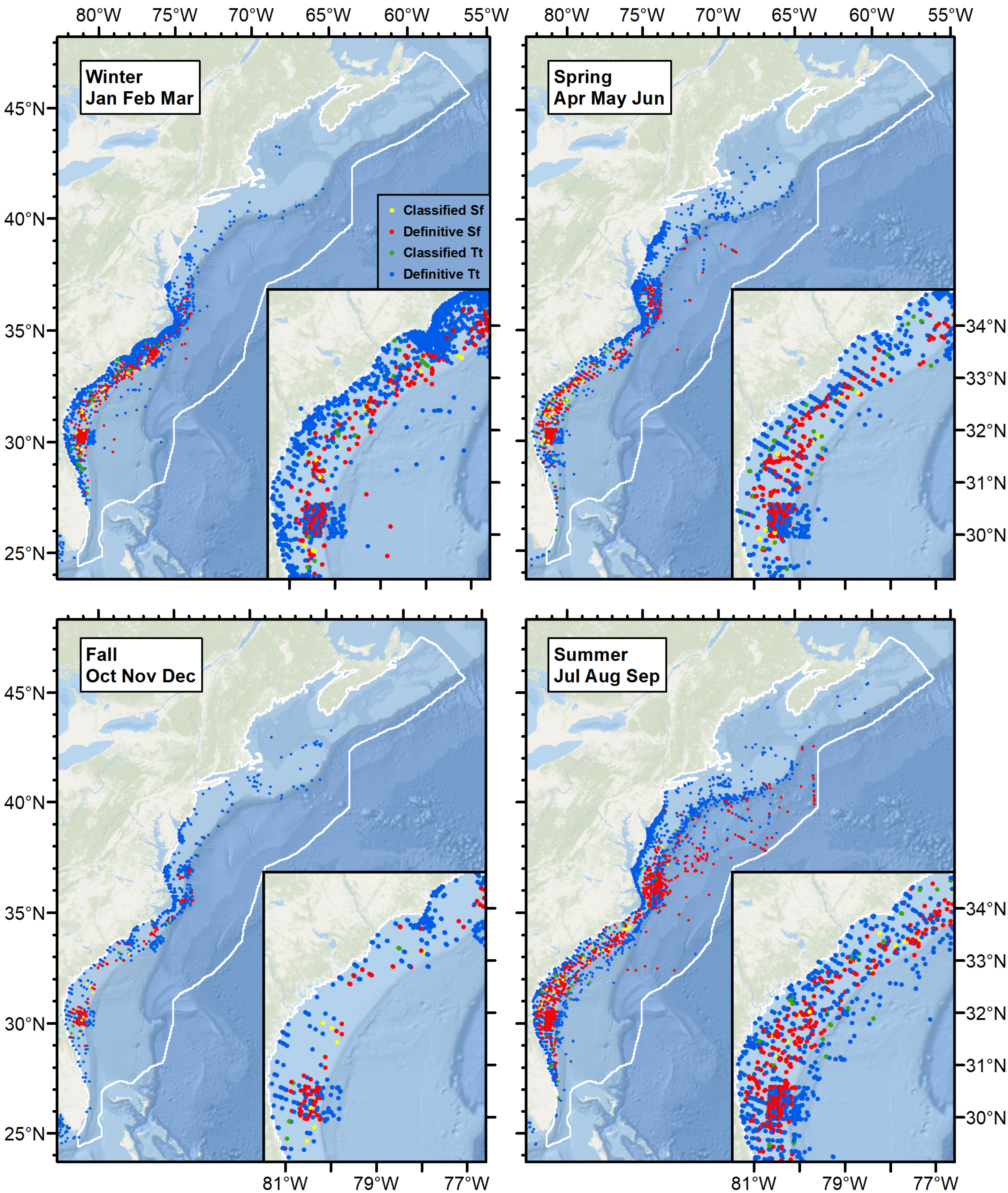


Figure 4: Definitive sightings used to train the model and ambiguous sightings classified by the model.

3 Detection Functions

3.1 With a Taxonomic Covariate

We fitted the detection functions in this section to pools of species with similar detectability characteristics and used the taxonomic identification as a covariate (ScientificName) to account for differences between them. We consulted the literature and observer teams to determine appropriate poolings. We usually employed this approach to boost the counts of observations in the detection functions, which increased the chance that other covariates such as Beaufort sea state could be used to account for differences in observing conditions. When defining the taxonomic covariate, we sometimes had too few observations of species to allocate each of them their own level of the covariate and had to group them together, again consulting the literature and observers for advice on species similarity. Also, when species were observed frequently enough to be allocated their own levels but statistical tests indicated no significant difference between the levels, we usually grouped them together into a single level.

3.1.1 Aerial Surveys

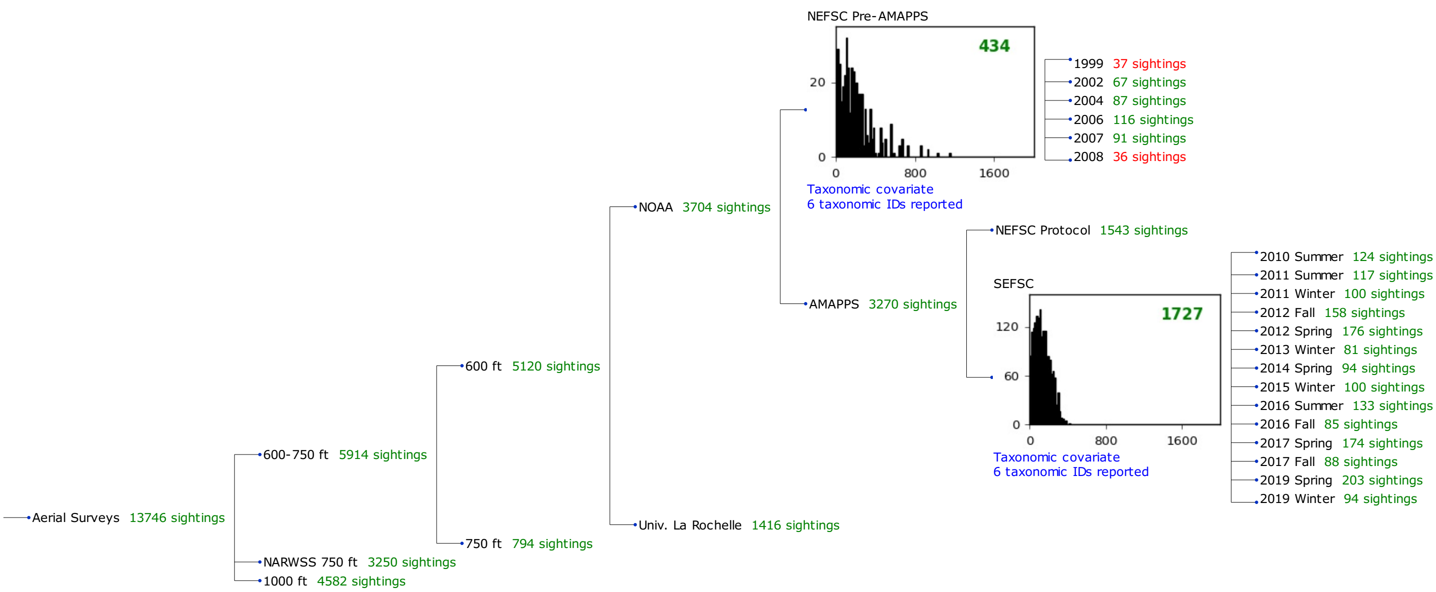


Figure 5: Detection hierarchy for aerial surveys, showing how they were pooled during detectability modeling, for detection functions that pooled multiple taxa and used used a taxonomic covariate to account for differences between them. Each histogram represents a detection function and summarizes the perpendicular distances of observations that were pooled to fit it, prior to truncation. Observation counts, also prior to truncation, are shown in green when they met the recommendation of Buckland et al. (2001) that detection functions utilize at least 60 sightings, and red otherwise. For rare taxa, it was not always possible to meet this recommendation, yielding higher statistical uncertainty. During the spatial modeling stage of the analysis, effective strip widths were computed for each survey using the closest detection function above it in the hierarchy (i.e. moving from right to left in the figure). Surveys that do not have a detection function above them in this figure were either addressed by a detection function presented in a different section of this report, or were omitted from the analysis.

3.1.1.1 NEFSC Pre-AMAPPS

After right-truncating observations greater than 600 m, we fitted the detection function to the 413 observations that remained (Table 6). The selected detection function (Figure 6) used a hazard rate key function with Beaufort (Figure 7) and ScientificName (Figure 8) as covariates.

Table 6: Observations used to fit the NEFSC Pre-AMAPPS detection function.

ScientificName	n
Delphinus, Lagenodelphis, Stenella	239
Lagenorhynchus	128
Tursiops, Steno	46
Total	**413**

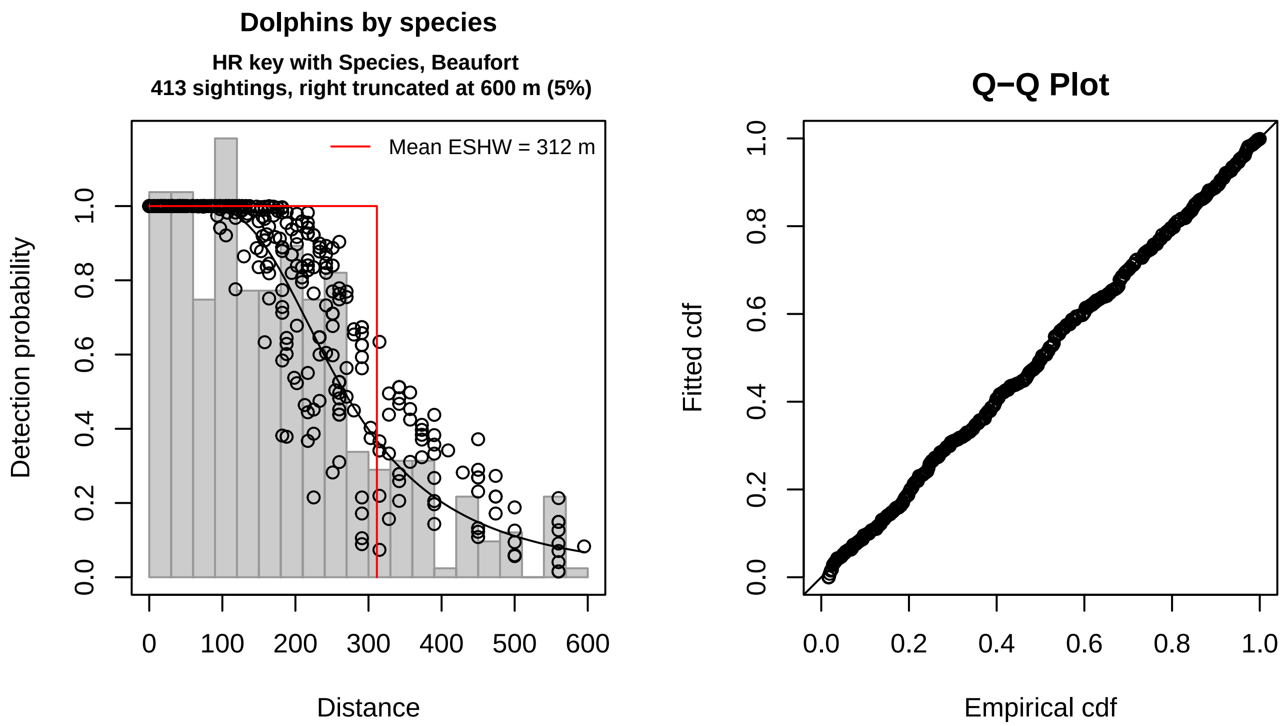


Figure 6: NEFSC Pre-AMAPPS detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  413
Distance range         :  0  -  600
AIC                    :  5043.994

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
                                estimate         se
(Intercept)                    5.3188665 0.15126469
ScientificNameLagenorhynchus  -0.1872175 0.11165678
ScientificNameTursiops, Steno -0.5457529 0.14785313
Beaufort                       0.1451869 0.05844944

Shape coefficient(s):
            estimate        se
(Intercept) 1.107015 0.1176733

                       Estimate          SE          CV
```

```
Average p              0.4982478  0.02373666 0.04764026
N in covered region 828.9047438 49.28440455 0.05945726

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.023324  p = 0.992716
```

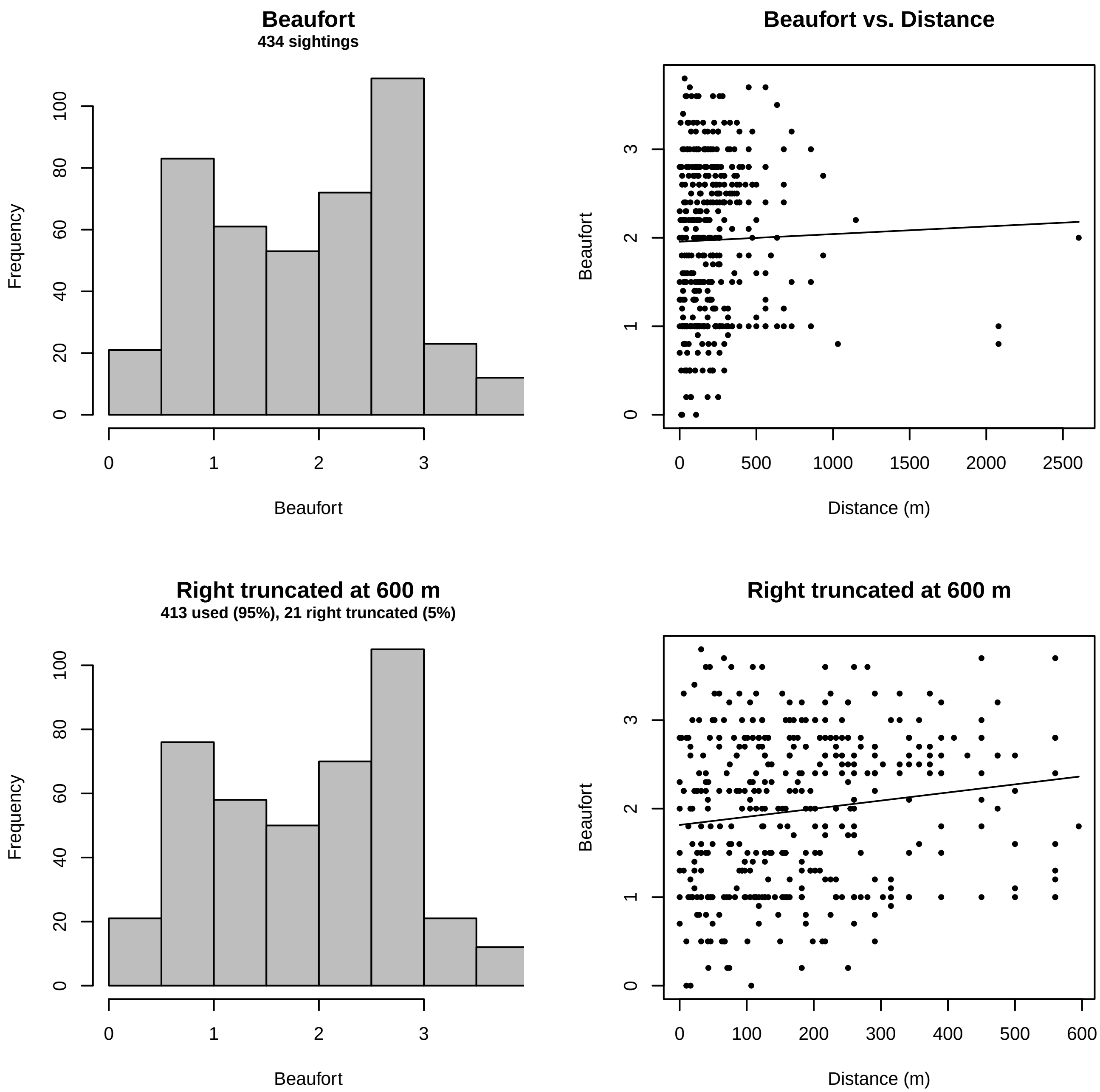


Figure 7: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the NEFSC Pre-AMAPPS detection function.

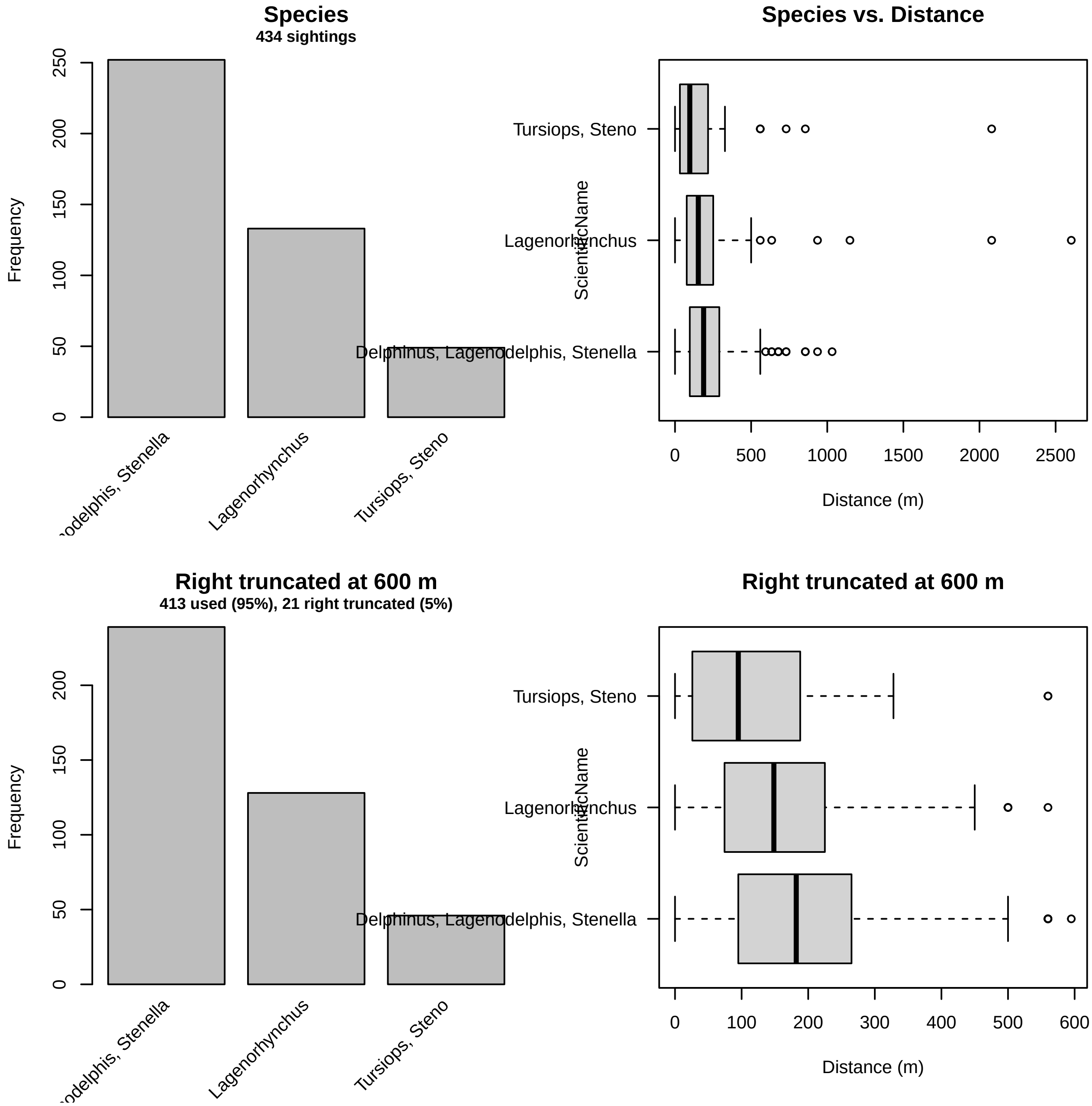


Figure 8: Distribution of the ScientificName covariate before (top row) and after (bottom row) observations were truncated to fit the NEFSC Pre-AMAPPS detection function.

3.1.1.2 SEFSC AMAPPS

After right-truncating observations greater than 325 m and left-truncating observations less than 15 m (Figure 10), we fitted the detection function to the 1628 observations that remained (Table 7). The selected detection function (Figure 9) used a hazard rate key function with Beaufort (Figure 11), ScientificName (Figure 12) and Season (Figure 13) as covariates.

Table 7: Observations used to fit the SEFSC AMAPPS detection function.

ScientificName	n
Delphinus, Tursiops, Lagenorhynchus, Steno	1422
Stenella, Lagenodelphis	206
Total	**1628**

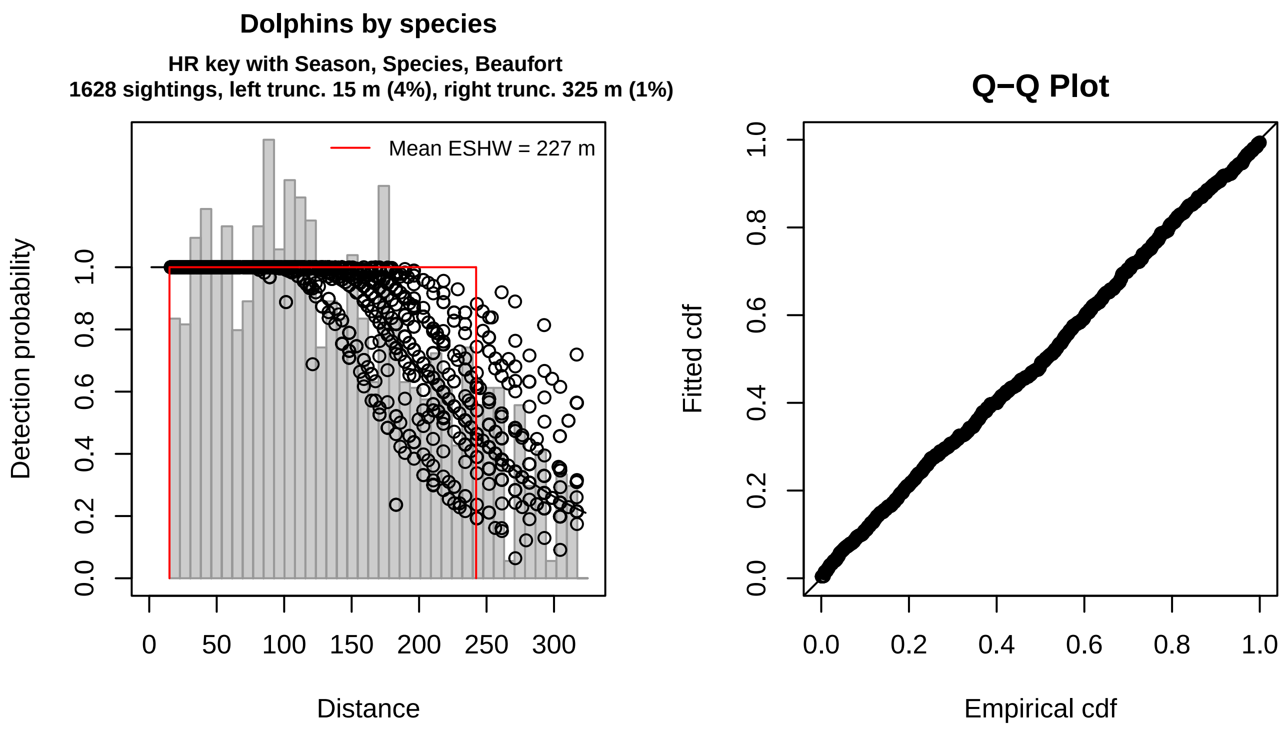


Figure 9: SEFSC AMAPPS detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  1628
Distance range         :  15  -  325
AIC                    :  18351.39

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
                                     estimate         se
(Intercept)                         5.4780735 0.08251975
SeasonSummer                        0.1269645 0.06172358
SeasonWinter                       -0.2356803 0.06102237
ScientificNameStenella, Lagenodelphis  0.2204074 0.08699872
Beaufort2                          -0.1192230 0.08713320
Beaufort3                          -0.1846083 0.08971655
Beaufort4                          -0.4027356 0.12330363

Shape coefficient(s):
            estimate        se
(Intercept) 1.266688 0.1150367

                       Estimate          SE         CV
Average p              0.720161  0.01522909 0.02114679
N in covered region 2260.605761 56.60731047 0.02504077

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.138923  p = 0.425167
```

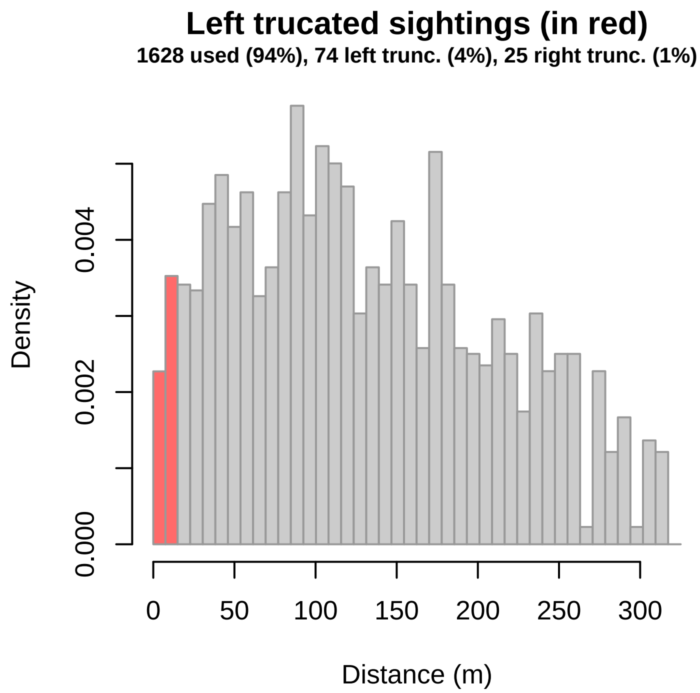


Figure 10: Density histogram of observations used to fit the SEFSC AMAPPS detection function, with the left-most bar showing observations at distances less than 15 m, which were left-truncated and excluded from the analysis [Buckland et al. (2001)]. (This bar may be very short if there were very few left-truncated sightings, or very narrow if the left truncation distance was very small; in either case it may not appear red.)

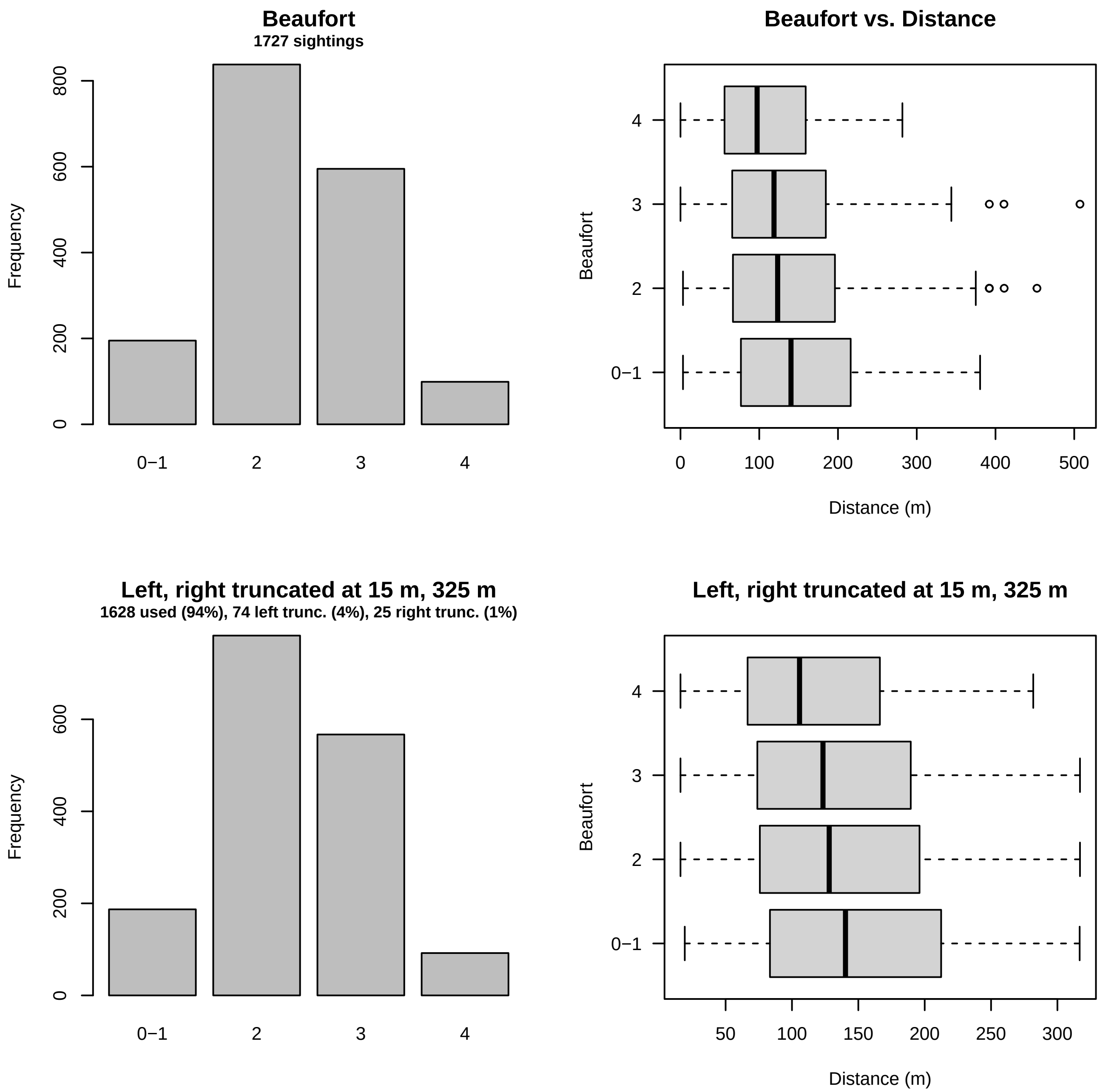


Figure 11: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the SEFSC AMAPPS detection function.

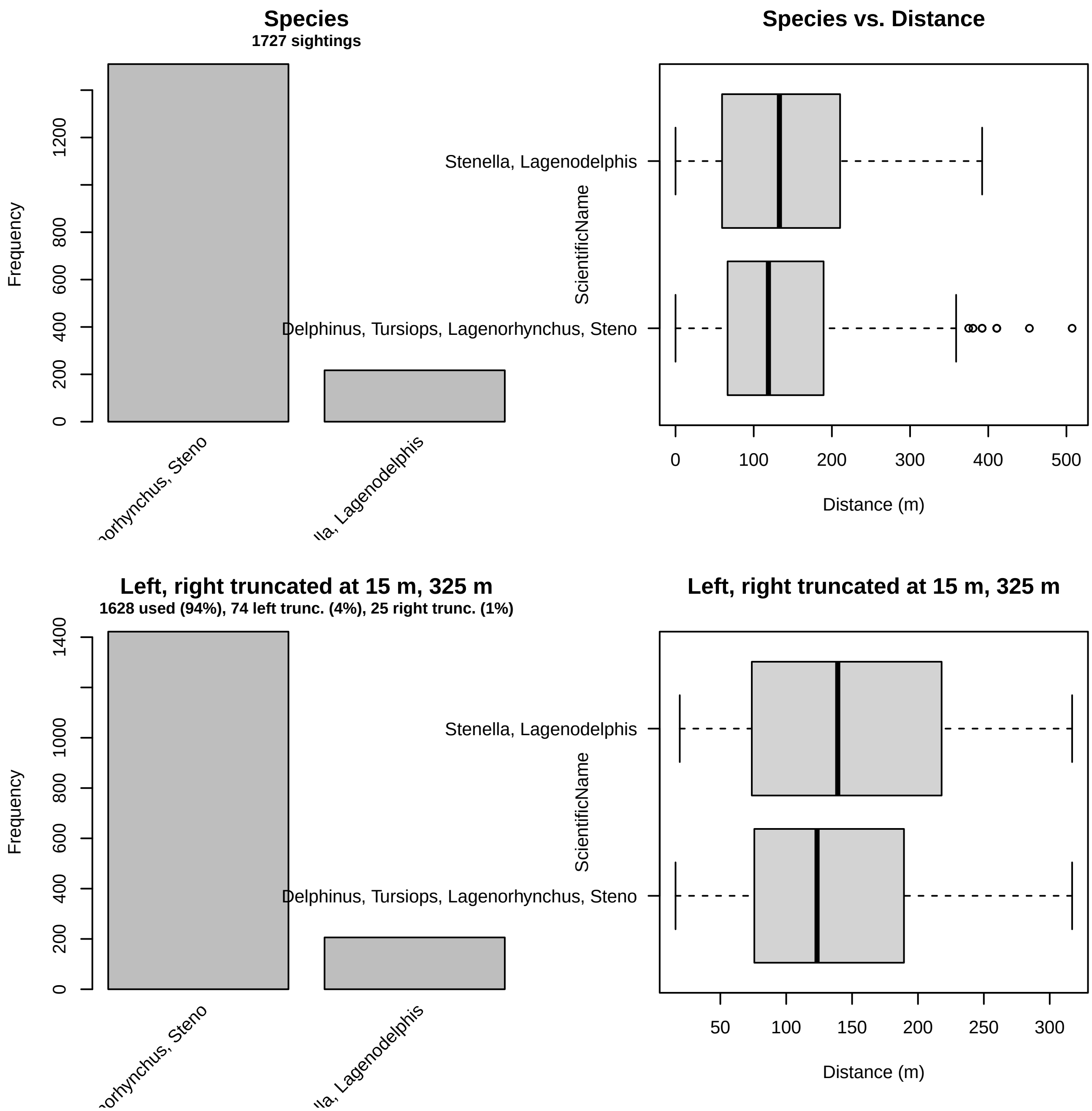


Figure 12: Distribution of the ScientificName covariate before (top row) and after (bottom row) observations were truncated to fit the SEFSC AMAPPS detection function.

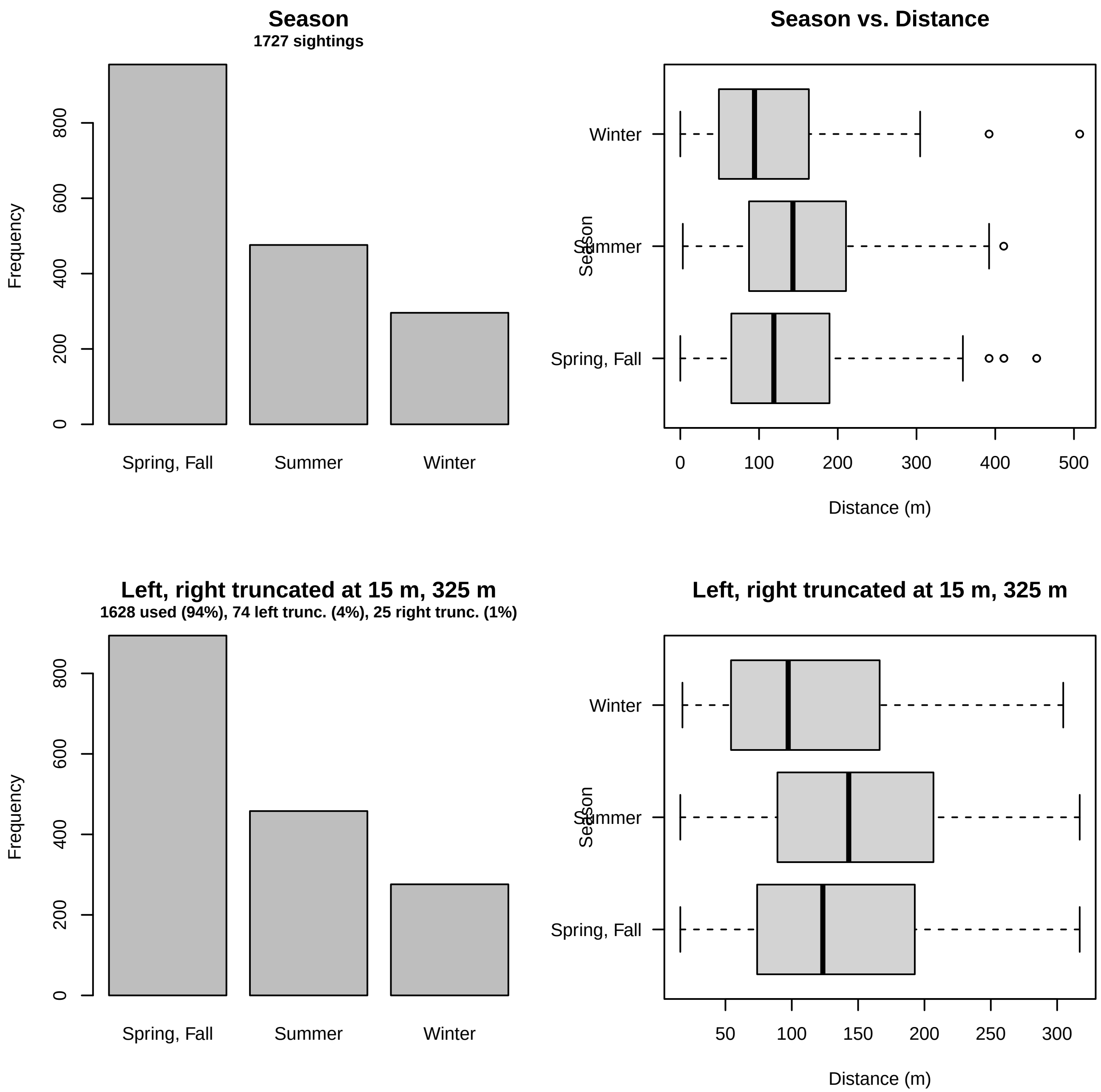


Figure 13: Distribution of the Season covariate before (top row) and after (bottom row) observations were truncated to fit the SEFSC AMAPPS detection function.

3.1.2 Shipboard Surveys

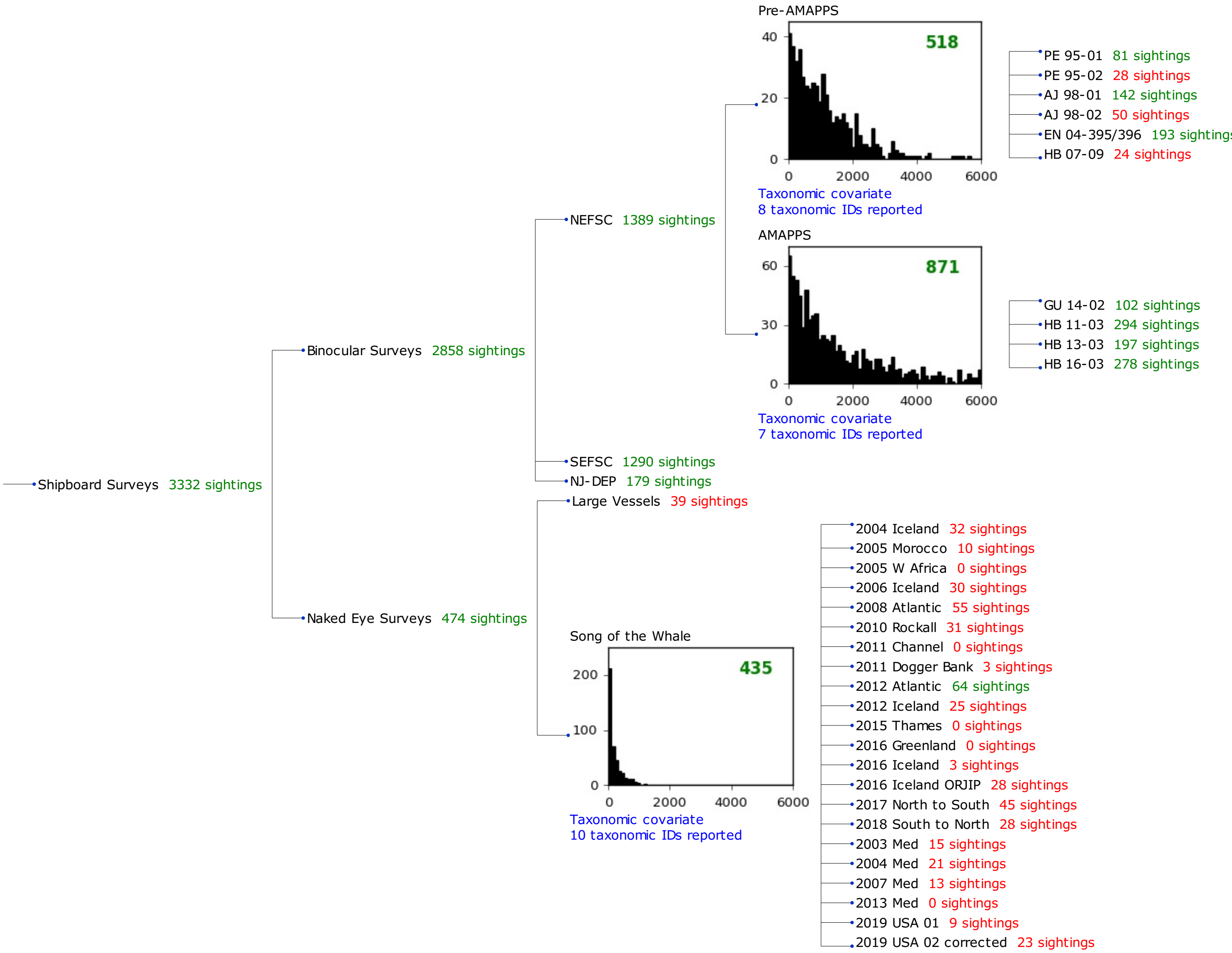


Figure 14: Detection hierarchy for shipboard surveys, showing how they were pooled during detectability modeling, for detection functions that pooled multiple taxa and used used a taxonomic covariate to account for differences between them. Each histogram represents a detection function and summarizes the perpendicular distances of observations that were pooled to fit it, prior to truncation. Observation counts, also prior to truncation, are shown in green when they met the recommendation of Buckland et al. (2001) that detection functions utilize at least 60 sightings, and red otherwise. For rare taxa, it was not always possible to meet this recommendation, yielding higher statistical uncertainty. During the spatial modeling stage of the analysis, effective strip widths were computed for each survey using the closest detection function above it in the hierarchy (i.e. moving from right to left in the figure). Surveys that do not have a detection function above them in this figure were either addressed by a detection function presented in a different section of this report, or were omitted from the analysis.

3.1.2.1 NEFSC Pre-AMAPPS

After right-truncating observations greater than 4000 m, we fitted the detection function to the 508 observations that remained (Table 8). The selected detection function (Figure 15) used a hazard rate key function with Beaufort (Figure 16), ScientificName (Figure 17) and VesselName (Figure 18) as covariates.

Table 8: Observations used to fit the NEFSC Pre-AMAPPS detection function.

ScientificName	n
Delphinus, Lagenorhynchus, Tursiops, Steno	365
Other Stenella, Lagenodelphis	130
Stenella frontalis	13
Total	**508**

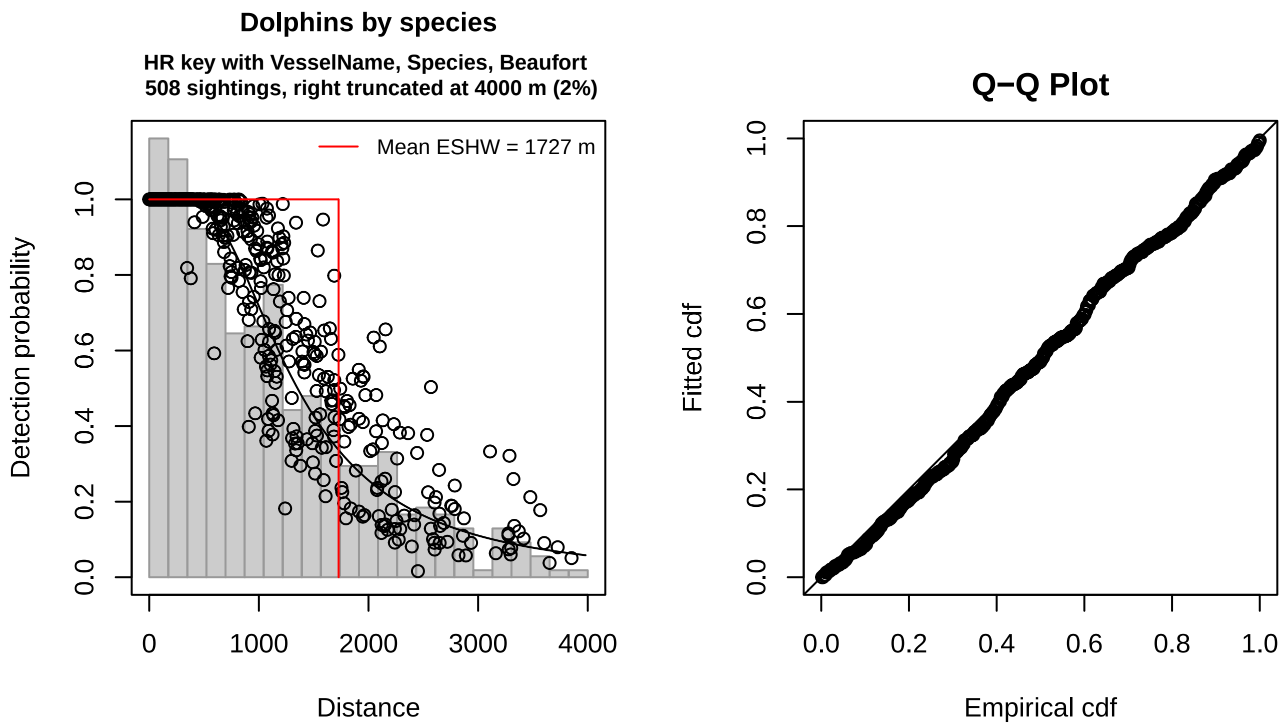


Figure 15: NEFSC Pre-AMAPPS detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  508
Distance range         :  0  -  4000
AIC                    :  8058.614

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
                                          estimate        se
(Intercept)                              7.3979634 0.1986065
VesselNameEndeavor, Bigelow              0.2529041 0.1095209
ScientificNameOther Stenella, Lagenodelphis  0.3555978 0.1258179
ScientificNameStenella frontalis        -0.8556981 0.3078540
Beaufort                                -0.1897812 0.0694737

Shape coefficient(s):
             estimate        se
(Intercept) 0.8752144 0.1006522
```

```
                       Estimate          SE         CV
Average p             0.4071518  0.02118698 0.05203705
N in covered region 1247.6919609 78.15195776 0.06263722

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.120847  p = 0.492001
```

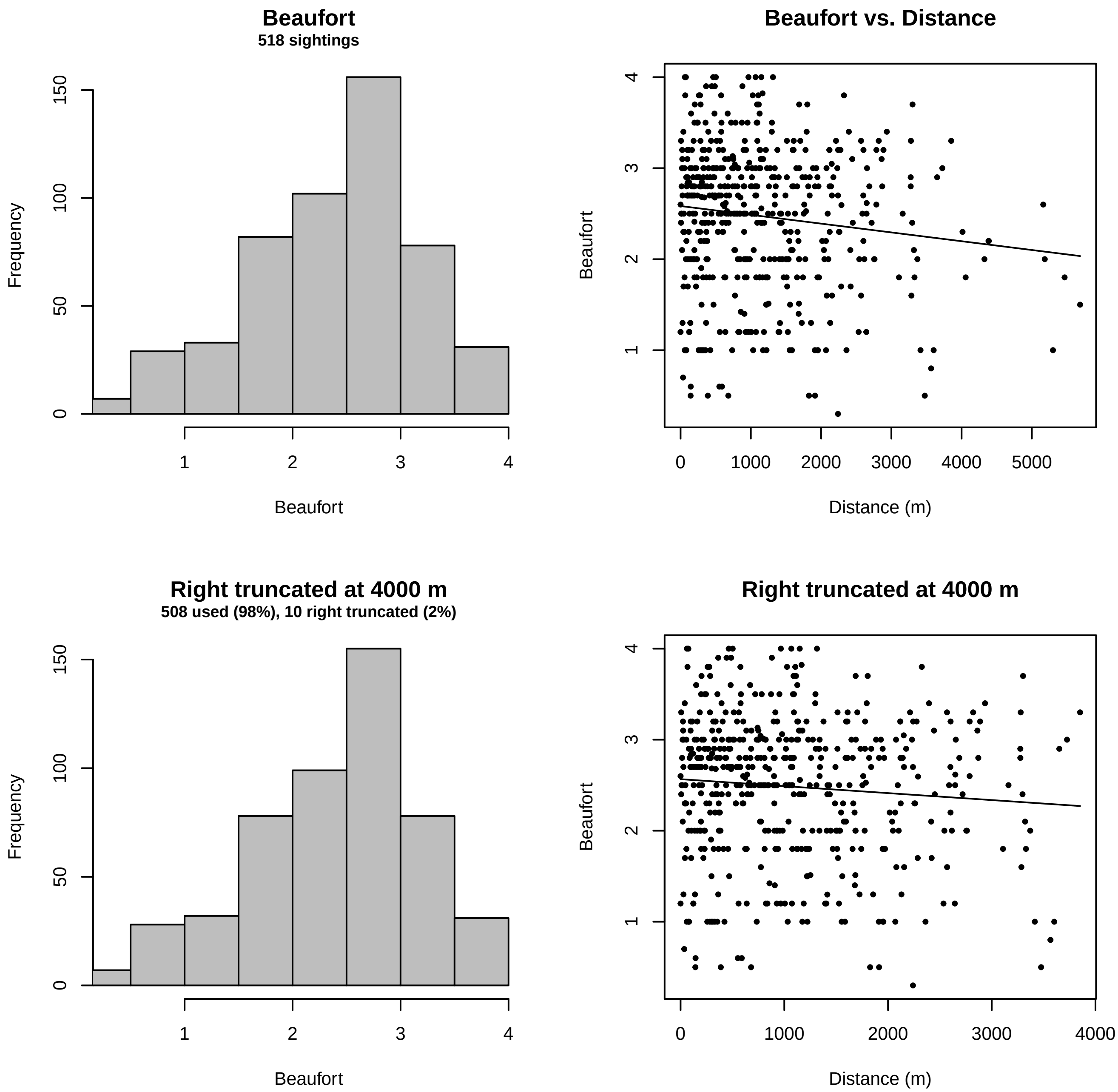


Figure 16: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the NEFSC Pre-AMAPPS detection function.

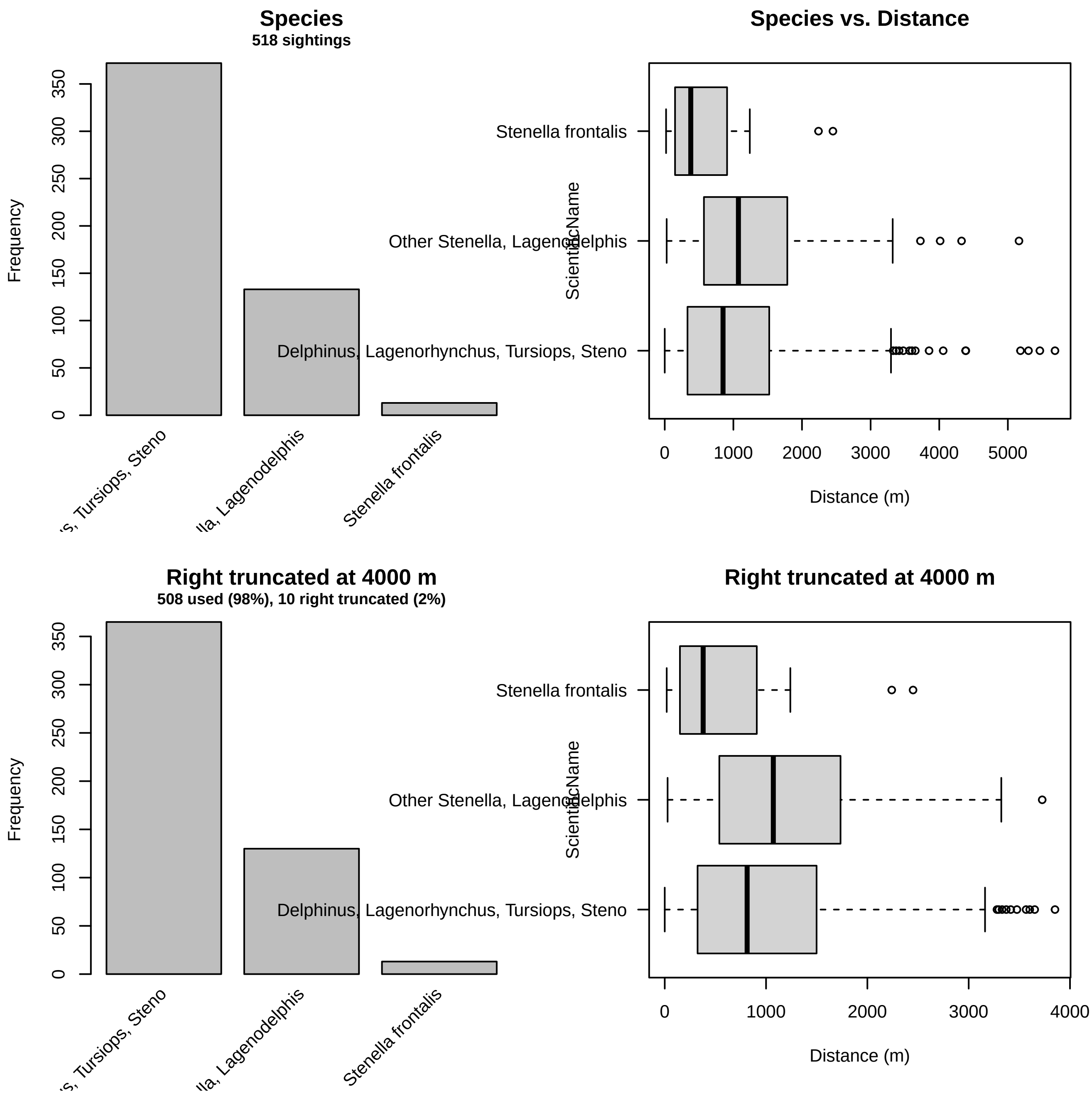


Figure 17: Distribution of the ScientificName covariate before (top row) and after (bottom row) observations were truncated to fit the NEFSC Pre-AMAPPS detection function.

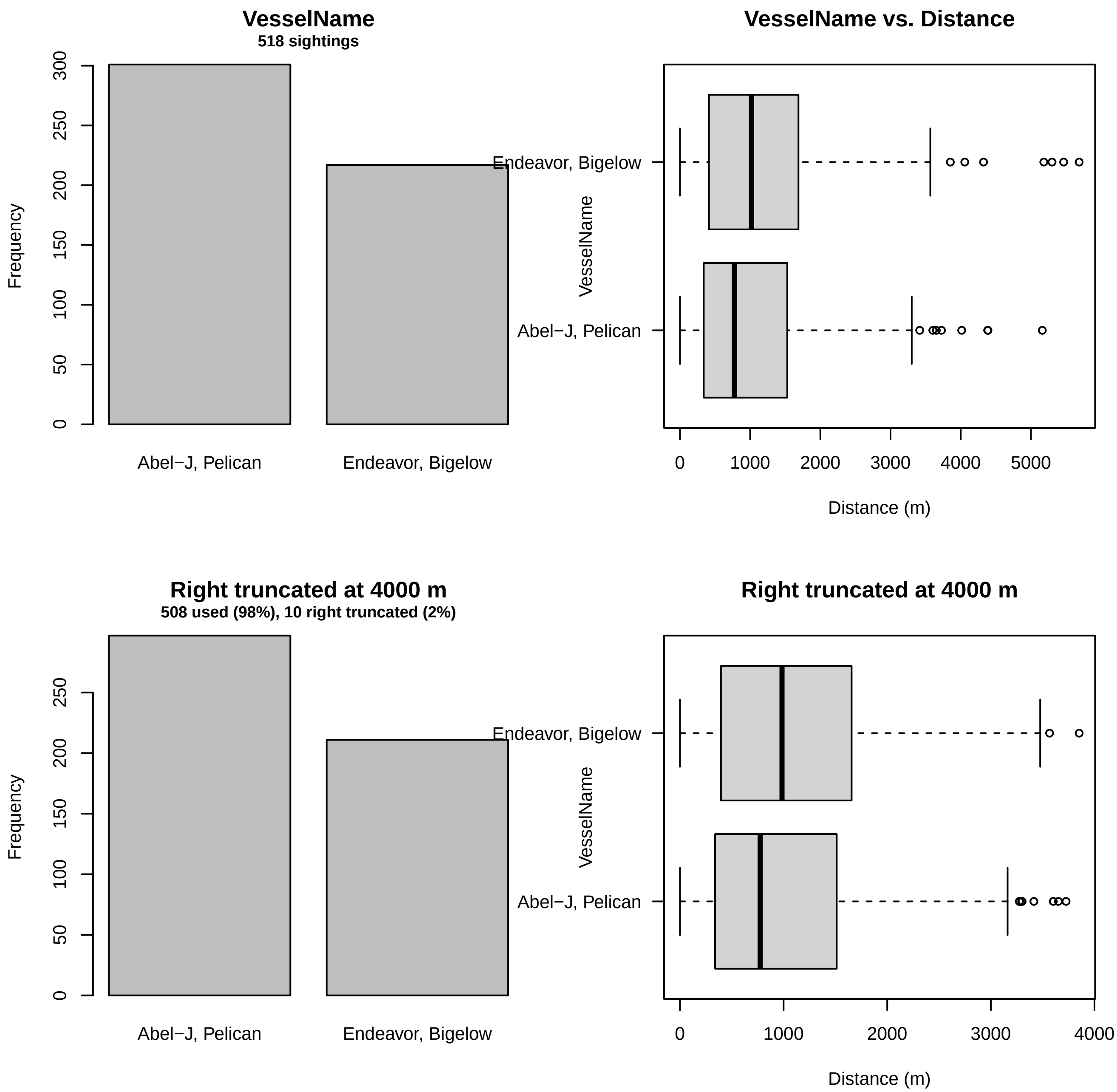


Figure 18: Distribution of the VesselName covariate before (top row) and after (bottom row) observations were truncated to fit the NEFSC Pre-AMAPPS detection function.

3.1.2.2 NEFSC AMAPPS

After right-truncating observations greater than 6000 m, we fitted the detection function to the 857 observations that remained (Table 9). The selected detection function (Figure 19) used a hazard rate key function with Beaufort (Figure 20) and ScientificName (Figure 21) as covariates.

Table 9: Observations used to fit the NEFSC AMAPPS detection function.

ScientificName	n
Delphinus, Lagenorhynchus	358
Other Stenella, Lagenodelphis	175
Stenella frontalis	53
Tursiops, Steno	271
Total	**857**

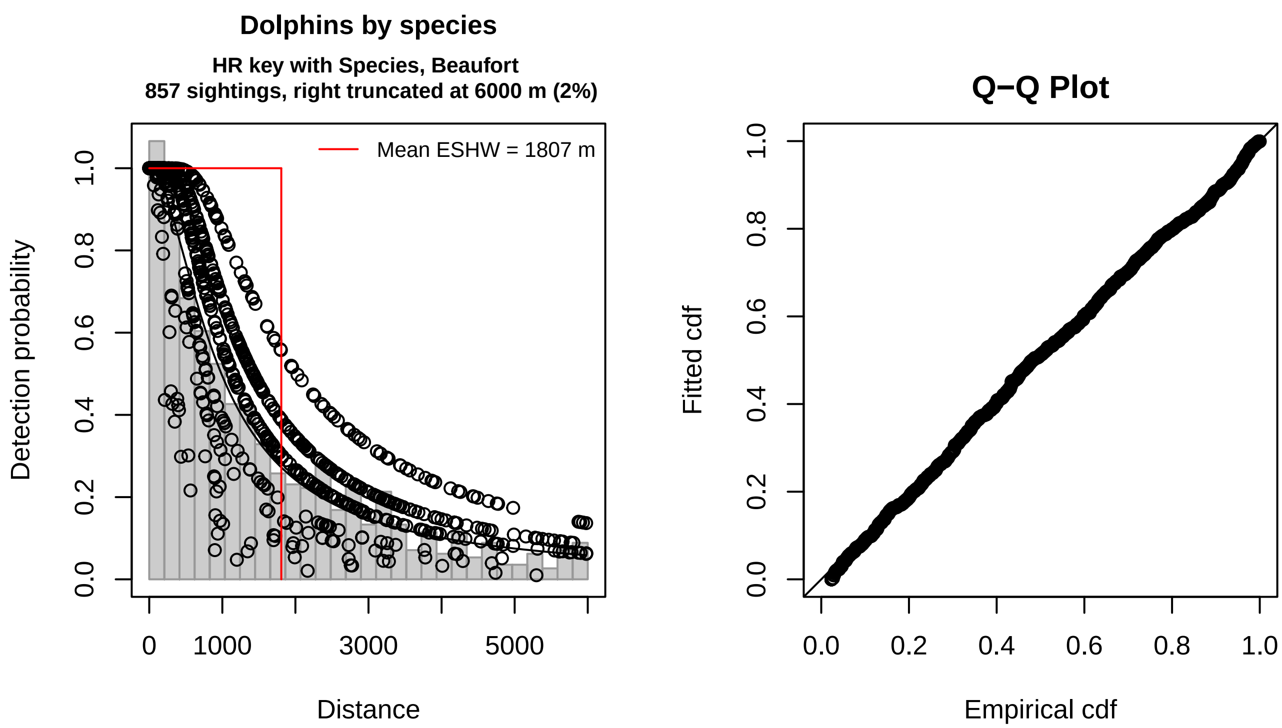


Figure 19: NEFSC AMAPPS detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  857
Distance range         :  0  -  6000
AIC                    :  14222.66

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
                                          estimate        se
(Intercept)                              7.0022801 0.1342692
ScientificNameOther Stenella, Lagenodelphis  0.3515378 0.1854896
ScientificNameStenella frontalis        -0.5910499 0.3033455
ScientificNameTursiops, Steno           -0.2176361 0.1602756
Beaufort3-4                             -0.5842019 0.1839783
Beaufort4-5                             -1.4374209 0.2667762

Shape coefficient(s):
            estimate        se
```

```
(Intercept) 0.356339 0.0663051

                        Estimate          SE         CV
Average p              0.2624967  0.01868208 0.07117073
N in covered region 3264.8026106 252.27662296 0.07727163

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.089267  p = 0.640081
```

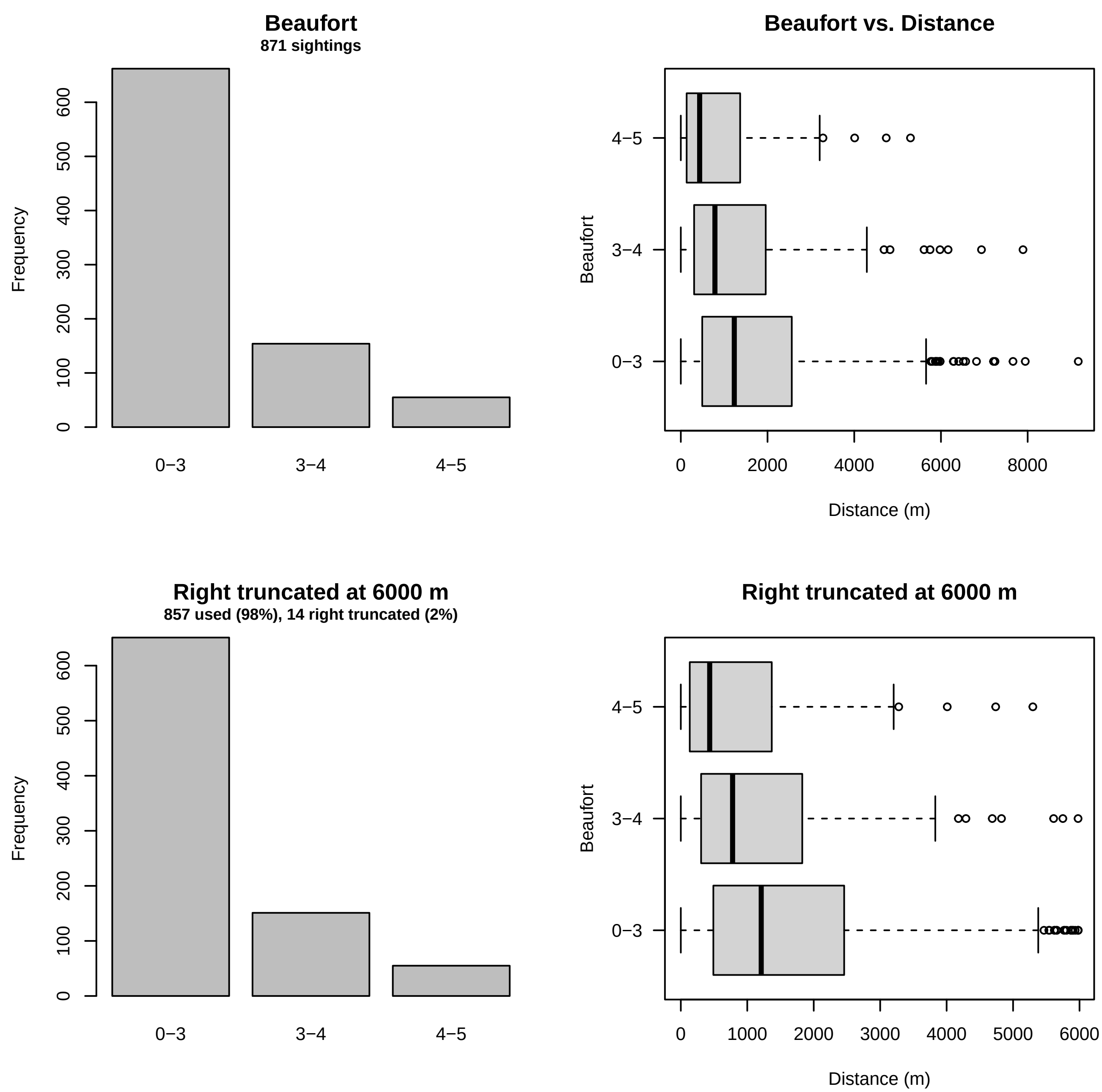


Figure 20: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the NEFSC AMAPPS detection function.

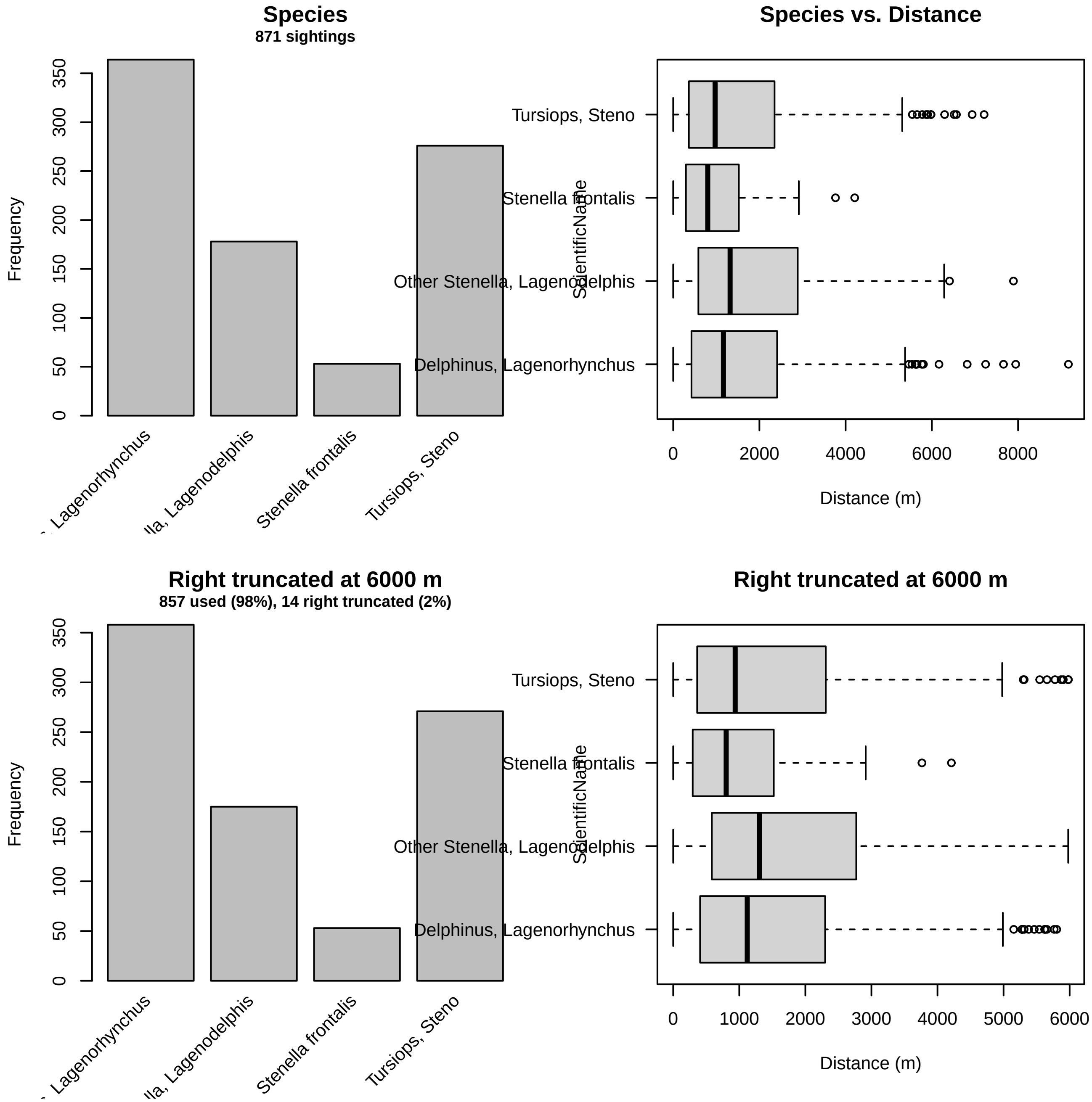


Figure 21: Distribution of the ScientificName covariate before (top row) and after (bottom row) observations were truncated to fit the NEFSC AMAPPS detection function.

3.1.2.3 Song of the Whale

After right-truncating observations greater than 700 m and left-truncating observations less than 1 m (Figure 23), we fitted the detection function to the 360 observations that remained (Table 10). The selected detection function (Figure 22) used a hazard rate key function with Beaufort (Figure 24), ScientificName (Figure 25) and Visibility (Figure 26) as covariates.

Table 10: Observations used to fit the Song of the Whale detection function.

ScientificName	n
All others	211
Delphinus	149
Total	**360**

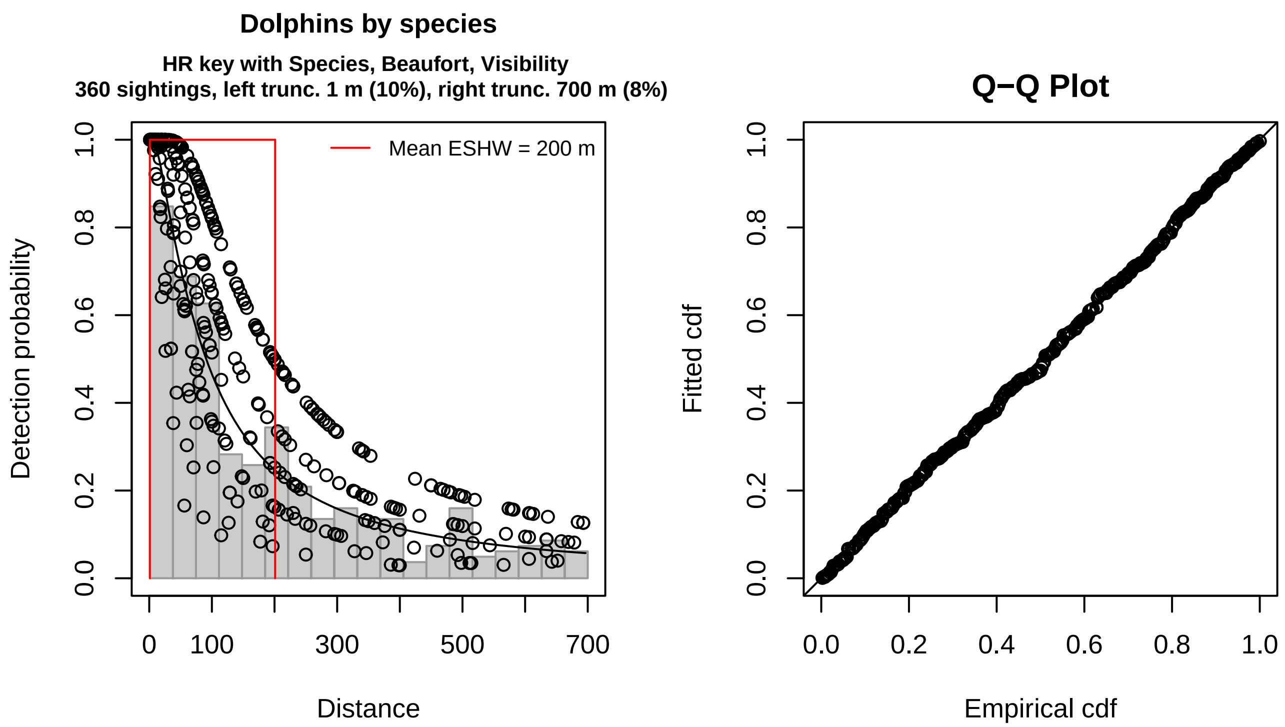


Figure 22: Song of the Whale detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  360
Distance range         :  1  -  700
AIC                    :  4434.06

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
                              estimate        se
(Intercept)                  5.0168382 0.2118228
ScientificNameDelphinus     -0.3746003 0.2526245
Beaufort3                   -0.6586604 0.2922112
Beaufort3.5-4               -1.3223280 0.3841776
VisibilityModerate (2-5nmi) -0.9687696 0.4363084

Shape coefficient(s):
             estimate         se
(Intercept) 0.2728327 0.09542948

                       Estimate            SE         CV
Average p              0.232512   0.02944422 0.1266352
N in covered region 1548.306965 209.54903632 0.1353408

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.019198  p = 0.997687
```

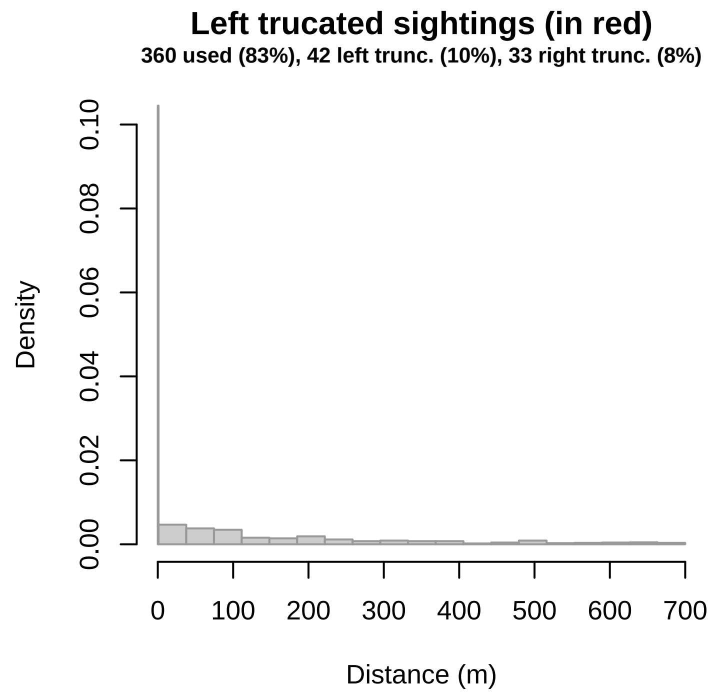


Figure 23: Density histogram of observations used to fit the Song of the Whale detection function, with the left-most bar showing observations at distances less than 1 m, which were left-truncated and not used to fit the detection function. (This bar may be very short if there were very few left-truncated sightings, or very narrow if the left truncation distance was very small; in either case it may not appear red.) These were excluded because they formed a problematic "spike" in detections close to the trackline, suggesting that animals approached the vessel (e.g. to bow-ride) prior to being detected. To address this, we fitted the detection function to the observations beyond the spike and assumed that within it, detection probability was 1, effectively treating it like a strip transect. We then added the left-truncated observations back into the analysis as if they occurred in this strip. This treatment may have resulted in an underestimation of detection probability.

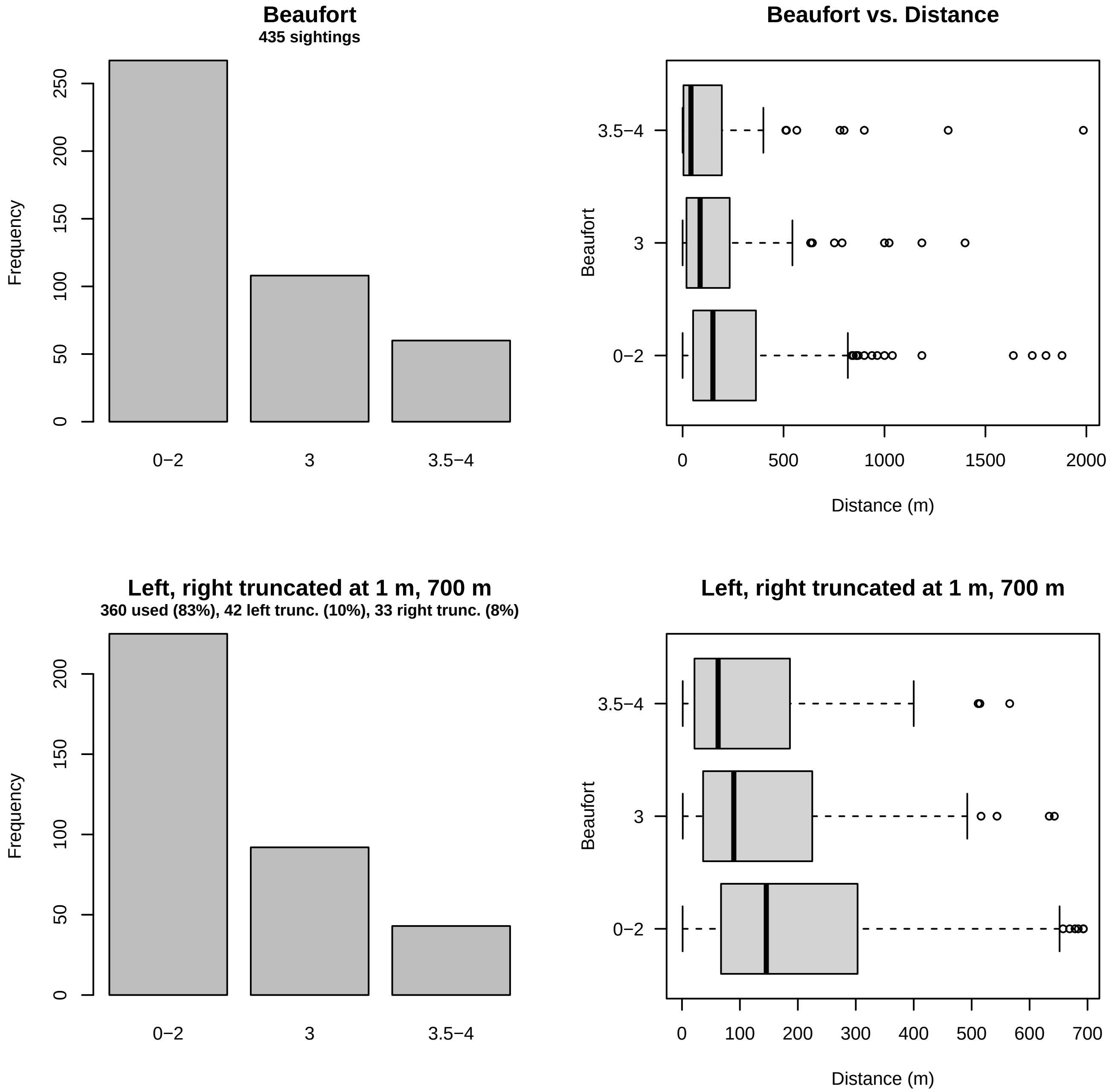


Figure 24: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the Song of the Whale detection function.

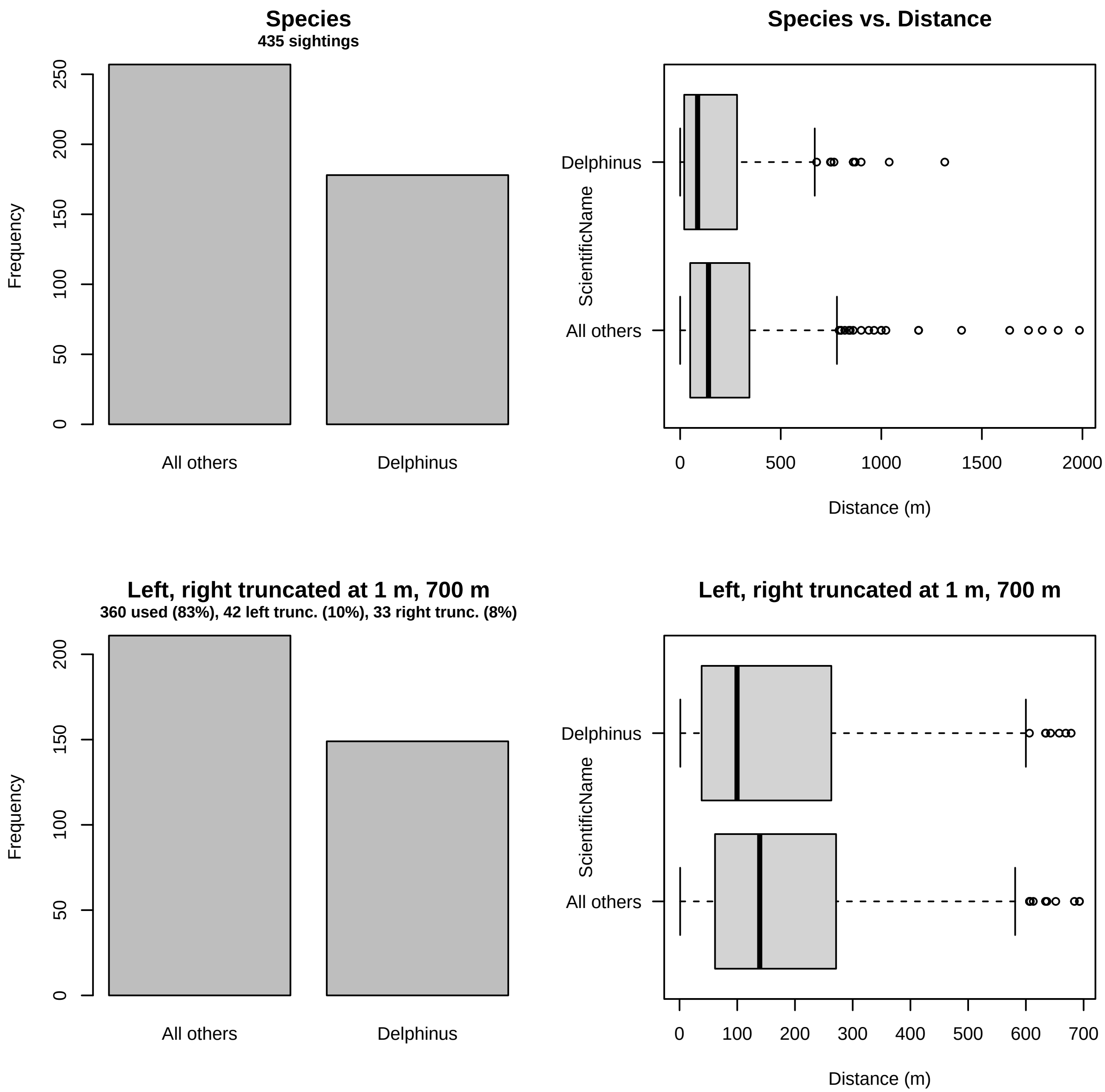


Figure 25: Distribution of the ScientificName covariate before (top row) and after (bottom row) observations were truncated to fit the Song of the Whale detection function.

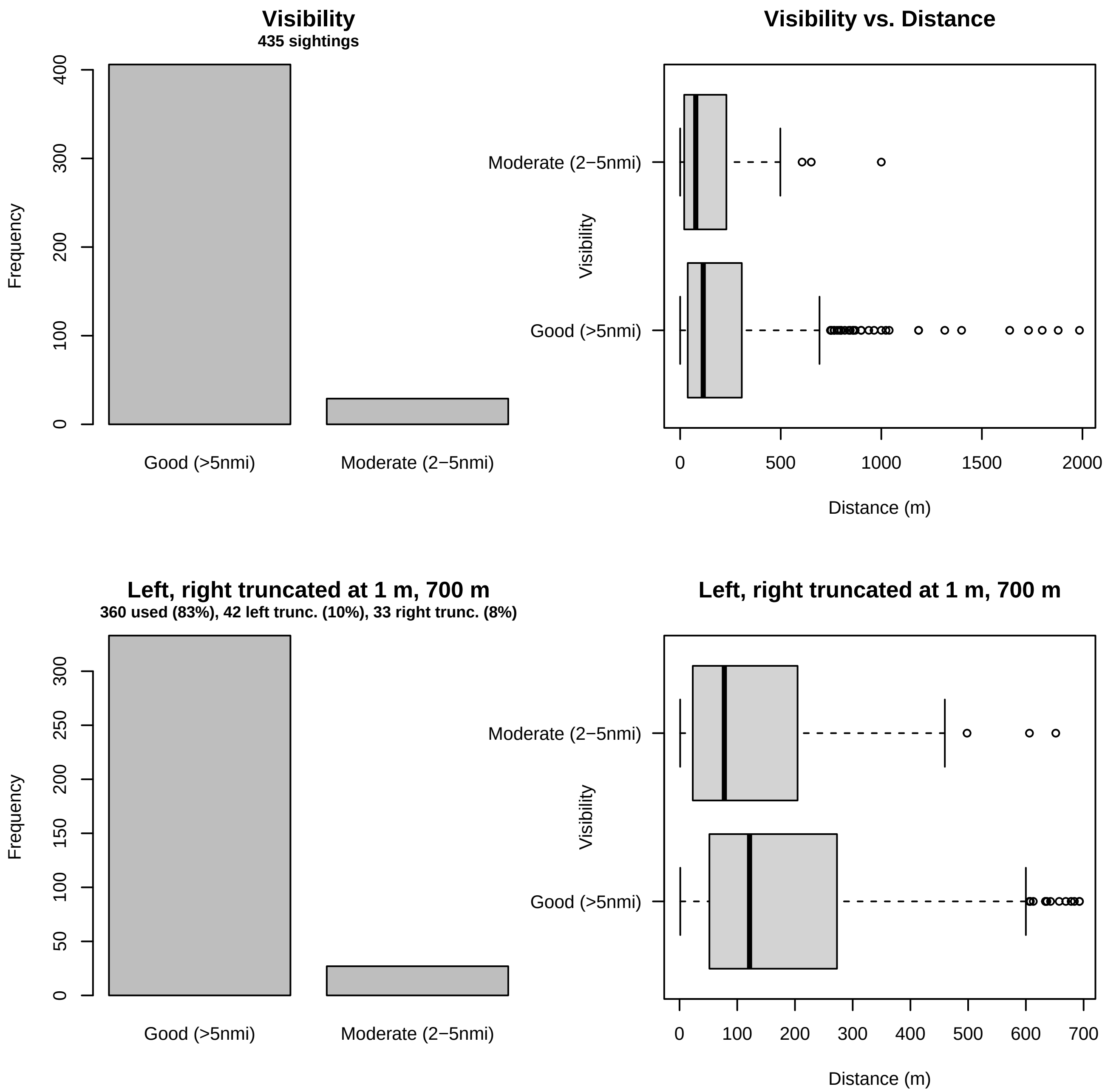


Figure 26: Distribution of the Visibility covariate before (top row) and after (bottom row) observations were truncated to fit the Song of the Whale detection function.

3.2 Without a Taxonomic Covariate

We fitted the detection functions in this section to pools of species with similar detectability characteristics but could not use a taxonomic identification as a covariate to account for differences between them. We usually took this approach after trying the taxonomic covariate and finding it had insufficient statistical power to be retained. We also resorted to it when the focal taxon being modeled had too few observations to be allocated its own taxonomic covariate level and was too poorly known for us to confidently determine which other taxa we could group it with.

3.2.1 Aerial Surveys

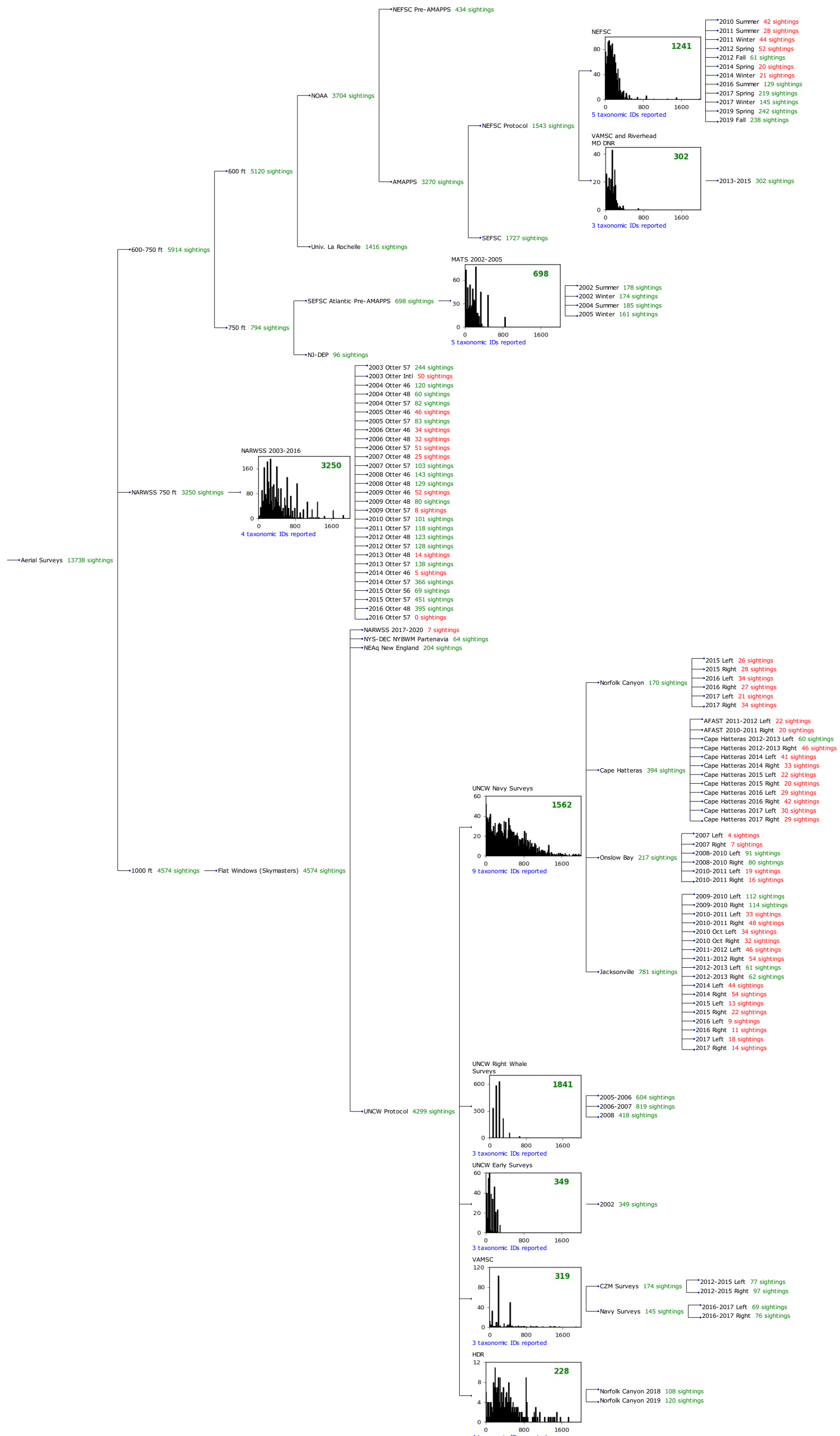


Figure 27: Detection hierarchy for aerial surveys, showing how they were pooled during detectability modeling, for detection functions that pooled multiple taxa but could not use a taxonomic covariate to account for differences between them. Each histogram represents a detection function and summarizes the perpendicular distances of observations that were pooled to fit it, prior to truncation. Observation counts, also prior to truncation, are shown in green when they met the recommendation of Buckland et al. (2001) that detection functions utilize at least 60 sightings, and red otherwise. For rare taxa, it was not always possible to meet this recommendation, yielding higher statistical uncertainty. During the spatial modeling stage of the analysis, effective strip widths were computed for each survey using the closest detection function above it in the hierarchy (i.e. moving from right to left in the figure). Surveys that do not have a detection function above them in this figure were either addressed by a detection function presented in a different section of this report, or were omitted from the analysis.

3.2.1.1 NEFSC AMAPPS

After right-truncating observations greater than 600 m, we fitted the detection function to the 1218 observations that remained (Table 11). The selected detection function (Figure 28) used a hazard rate key function with Season (Figure 29) as a covariate.

Table 11: Observations used to fit the NEFSC AMAPPS detection function.

ScientificName	n
Delphinus delphis	817
Lagenorhynchus acutus	280
Lagenorhynchus albirostris	3
Stenella coeruleoalba	13
Tursiops truncatus	105
Total	**1218**

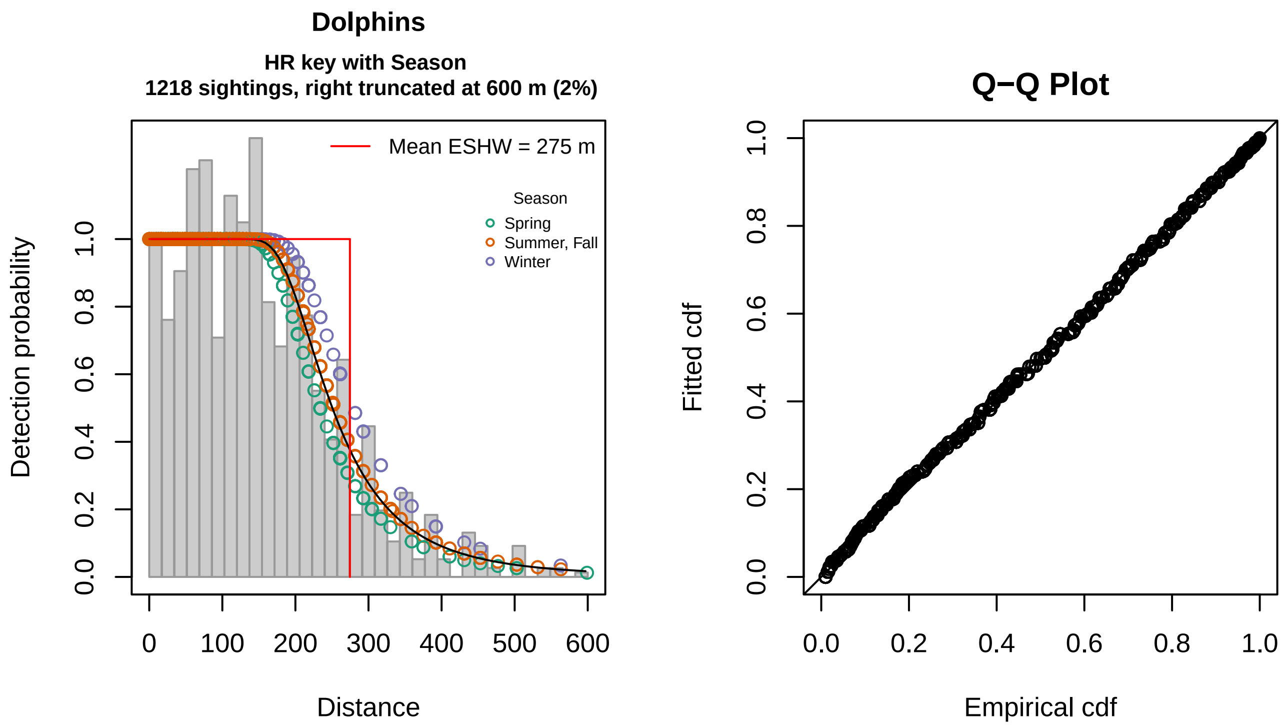


Figure 28: NEFSC AMAPPS detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  1218
Distance range         :  0  -  600
AIC                    :  14460.69

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
                     estimate         se
(Intercept)        5.36944749 0.04422696
SeasonSummer, Fall 0.08083579 0.04638562
SeasonWinter       0.17600218 0.07702020
```

```
Shape coefficient(s):
            estimate       se
(Intercept) 1.452854 0.065484

                       Estimate          SE         CV
Average p              0.456561  0.00970389 0.02125431
N in covered region 2667.770370 79.97999993 0.02998009

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.126854  p = 0.468488
```

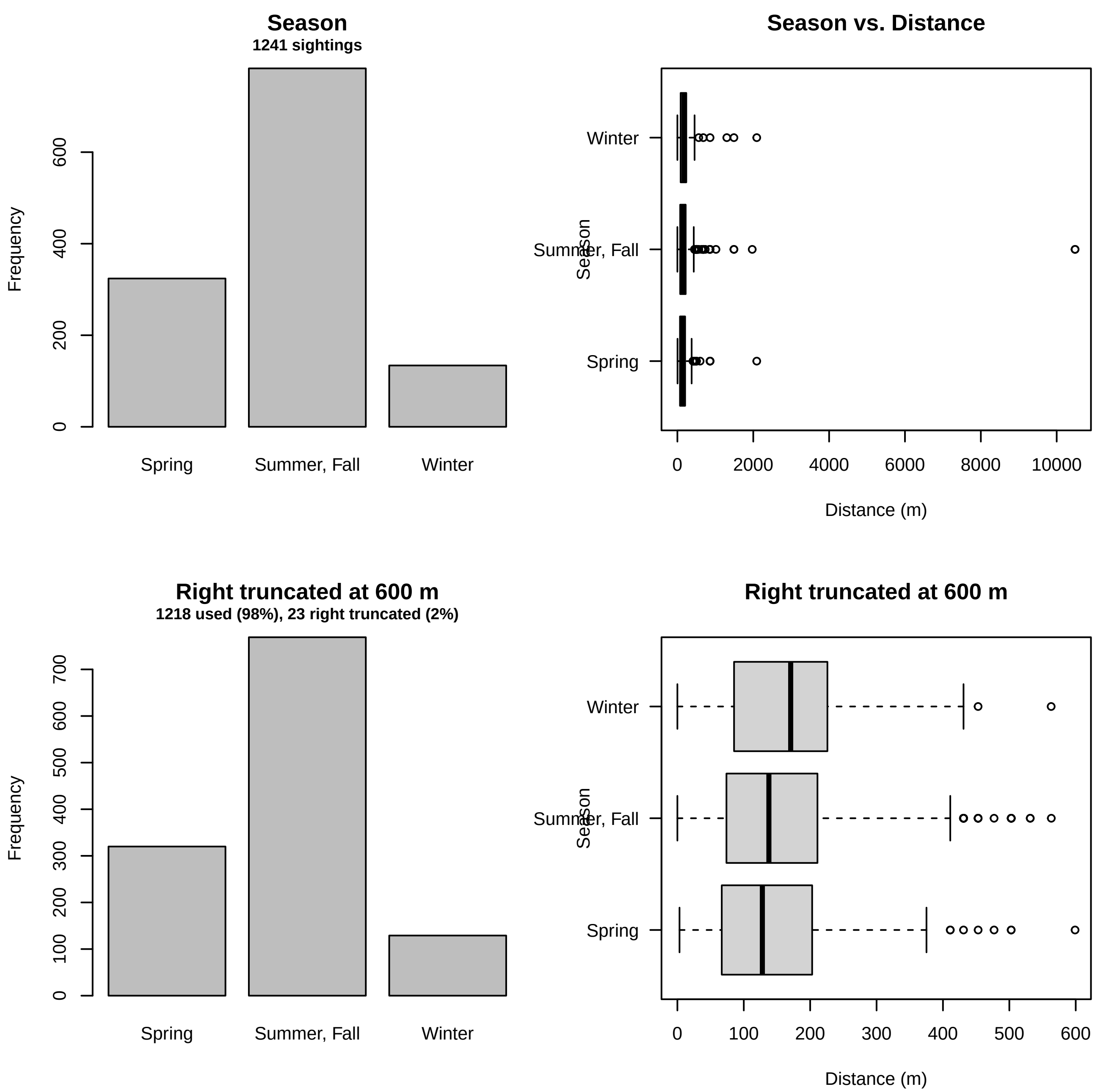


Figure 29: Distribution of the Season covariate before (top row) and after (bottom row) observations were truncated to fit the NEFSC AMAPPS detection function.

3.2.1.2 VAMSC and Riverhead MD DNR

After right-truncating observations greater than 400 m, we fitted the detection function to the 301 observations that remained (Table 12). The selected detection function (Figure 30) used a hazard rate key function with no covariates.

Table 12: Observations used to fit the VAMSC and Riverhead MD DNR detection function.

ScientificName	n
Delphinus delphis	22
Stenella frontalis	1
Tursiops truncatus	278
Total	**301**

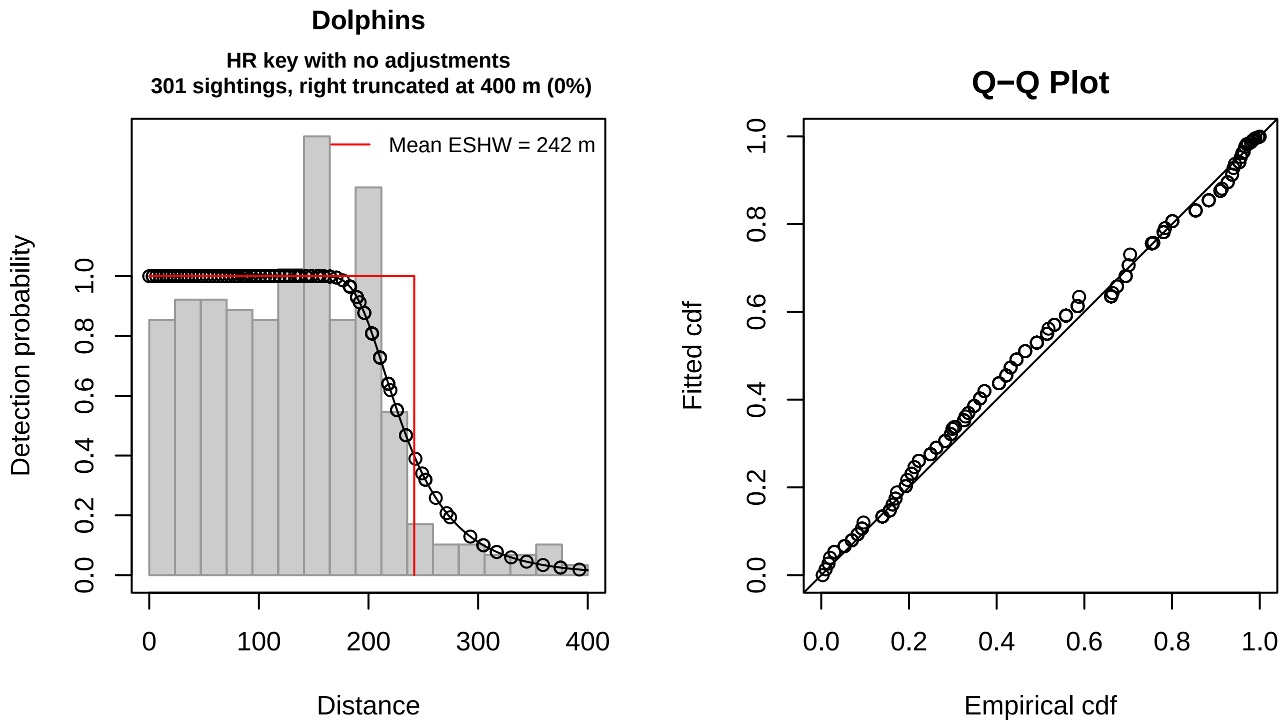


Figure 30: VAMSC and Riverhead MD DNR detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  301
Distance range         :  0  -  400
AIC                    :  3426.124

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
            estimate         se
(Intercept) 5.388208 0.04209556

Shape coefficient(s):
            estimate        se
(Intercept)  1.91525 0.1331166
```

```
                        Estimate         SE         CV
Average p              0.6042969  0.0203517 0.03367831
N in covered region 498.0995265 24.6489147 0.04948592

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.302011  p = 0.133421
```

3.2.1.3 MATS 2002-2005

After right-truncating observations greater than 629 m, we fitted the detection function to the 684 observations that remained (Table 13). The selected detection function (Figure 31) used a hazard rate key function with Beaufort (Figure 32) as a covariate.

Table 13: Observations used to fit the MATS 2002-2005 detection function.

ScientificName	n
Delphinus delphis	2
Stenella attenuata	2
Stenella frontalis	104
Tursiops truncatus	576
Total	**684**

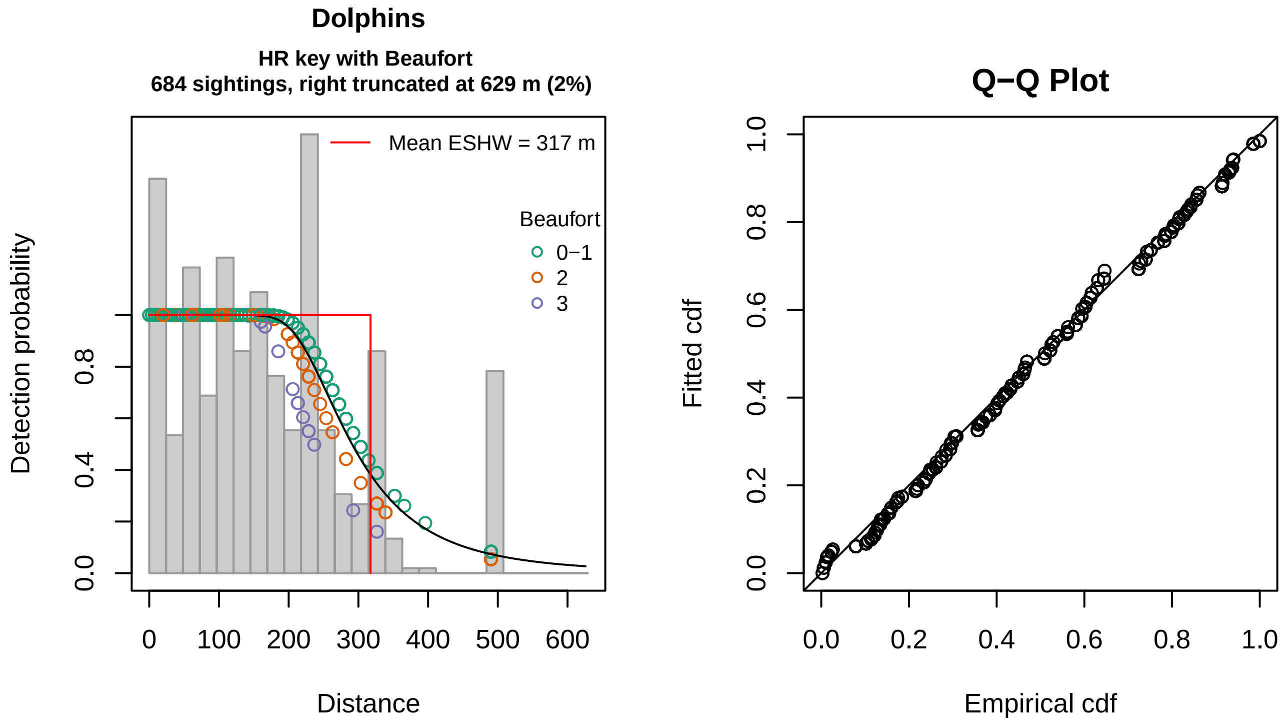


Figure 31: MATS 2002-2005 detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  684
Distance range         :  0  -  629
AIC                    :  8306.088

Detection function:
```

```
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
              estimate         se
(Intercept)  5.6213531 0.04325709
Beaufort2   -0.1046854 0.06814971
Beaufort3   -0.2421057 0.13060115

Shape coefficient(s):
            estimate         se
(Intercept) 1.449025 0.08965229

                        Estimate         SE         CV
Average p              0.5026836  0.0147185 0.02927984
N in covered region 1360.6968013 54.2106880 0.03984039

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.194502  p = 0.278380
```

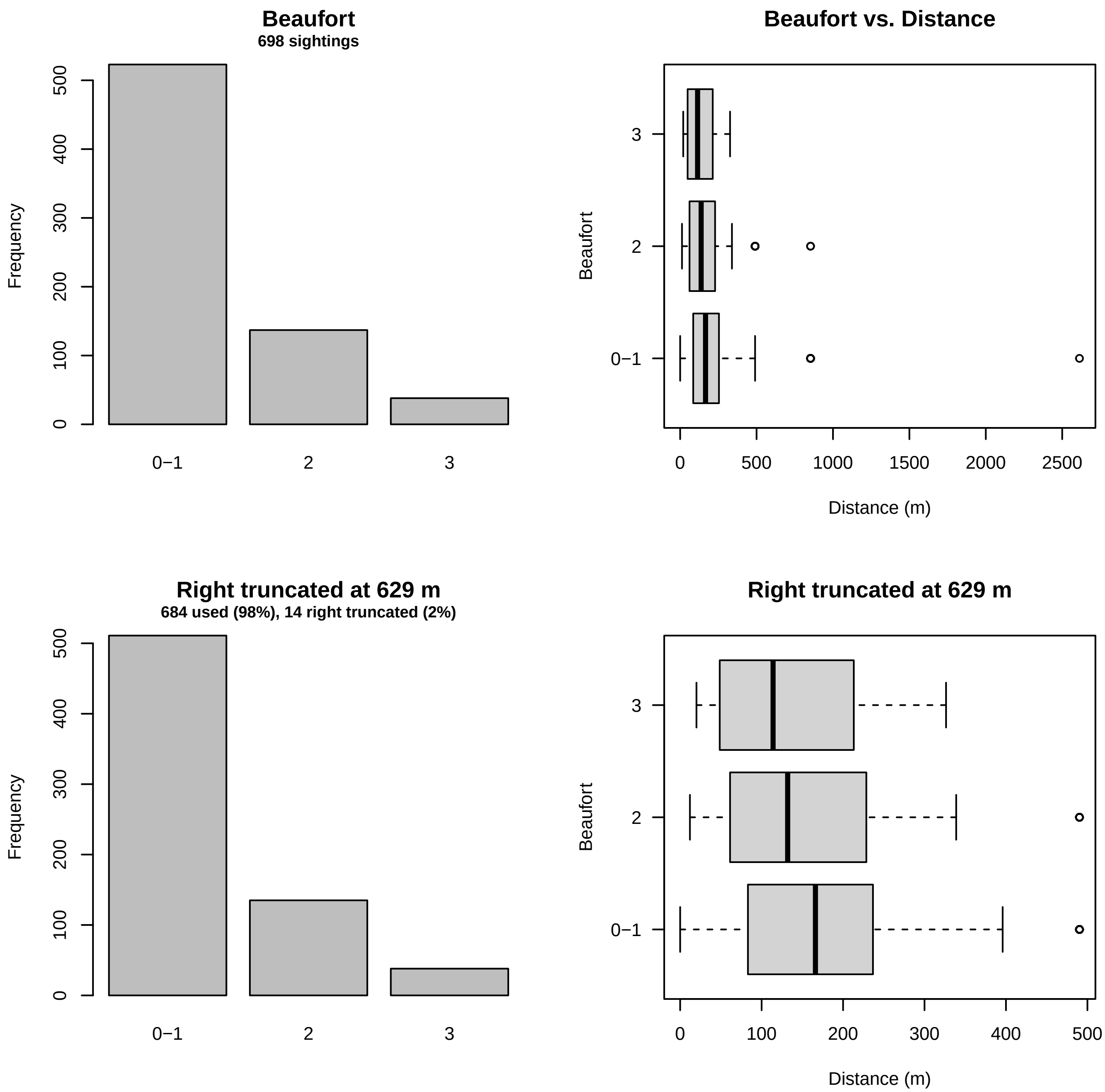


Figure 32: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the MATS 2002-2005 detection function.

3.2.1.4 NARWSS 2003-2016

After right-truncating observations greater than 1367 m and left-truncating observations less than 61 m (Figure 34), we fitted the detection function to the 3073 observations that remained (Table 14). The selected detection function (Figure 33) used a hazard rate key function with Beaufort (Figure 35) and Season (Figure 36) as covariates.

Table 14: Observations used to fit the NARWSS 2003-2016 detection function.

ScientificName	n
Delphinus delphis	607
Lagenorhynchus acutus	2404
Lagenorhynchus albirostris	6
Tursiops truncatus	56
Total	**3073**

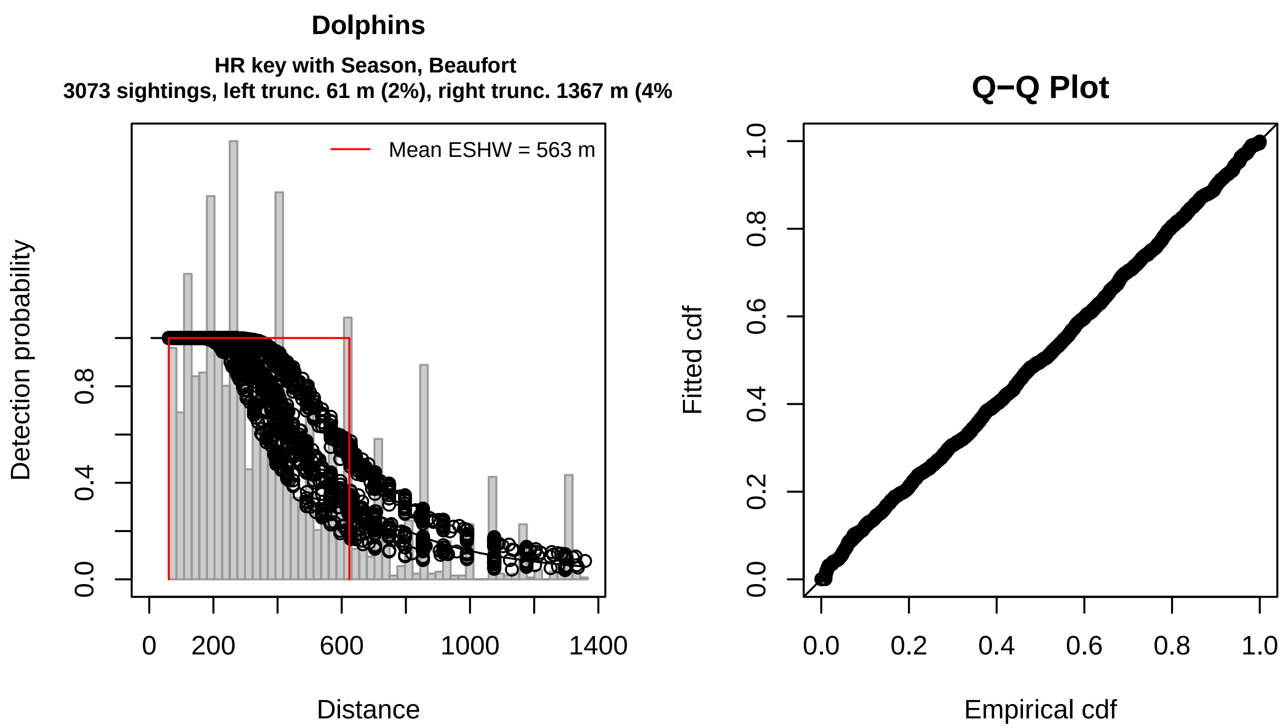


Figure 33: NARWSS 2003-2016 detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  3073
Distance range         :  61  -  1367
AIC                    :  41850.8

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
                estimate         se
(Intercept)   6.10469263 0.07579397
SeasonSpring  0.06689438 0.05622050
SeasonSummer  0.29278056 0.05383279
SeasonWinter -0.15259970 0.06804643
Beaufort     -0.03572691 0.02383833

Shape coefficient(s):
            estimate        se
(Intercept) 1.009361 0.0398862
```

```
                        Estimate           SE         CV
Average p              0.4196247 8.827249e-03 0.02103606
N in covered region 7323.2113220 1.845410e+02 0.02519946

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.246036  p = 0.193531
```

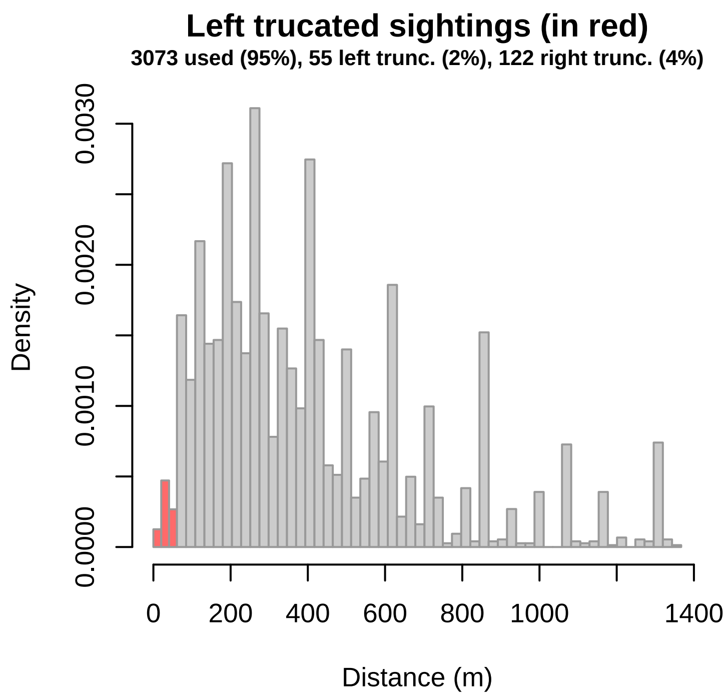


Figure 34: Density histogram of observations used to fit the NARWSS 2003-2016 detection function, with the left-most bar showing observations at distances less than 61 m, which were left-truncated and excluded from the analysis [Buckland et al. (2001)]. (This bar may be very short if there were very few left-truncated sightings, or very narrow if the left truncation distance was very small; in either case it may not appear red.)

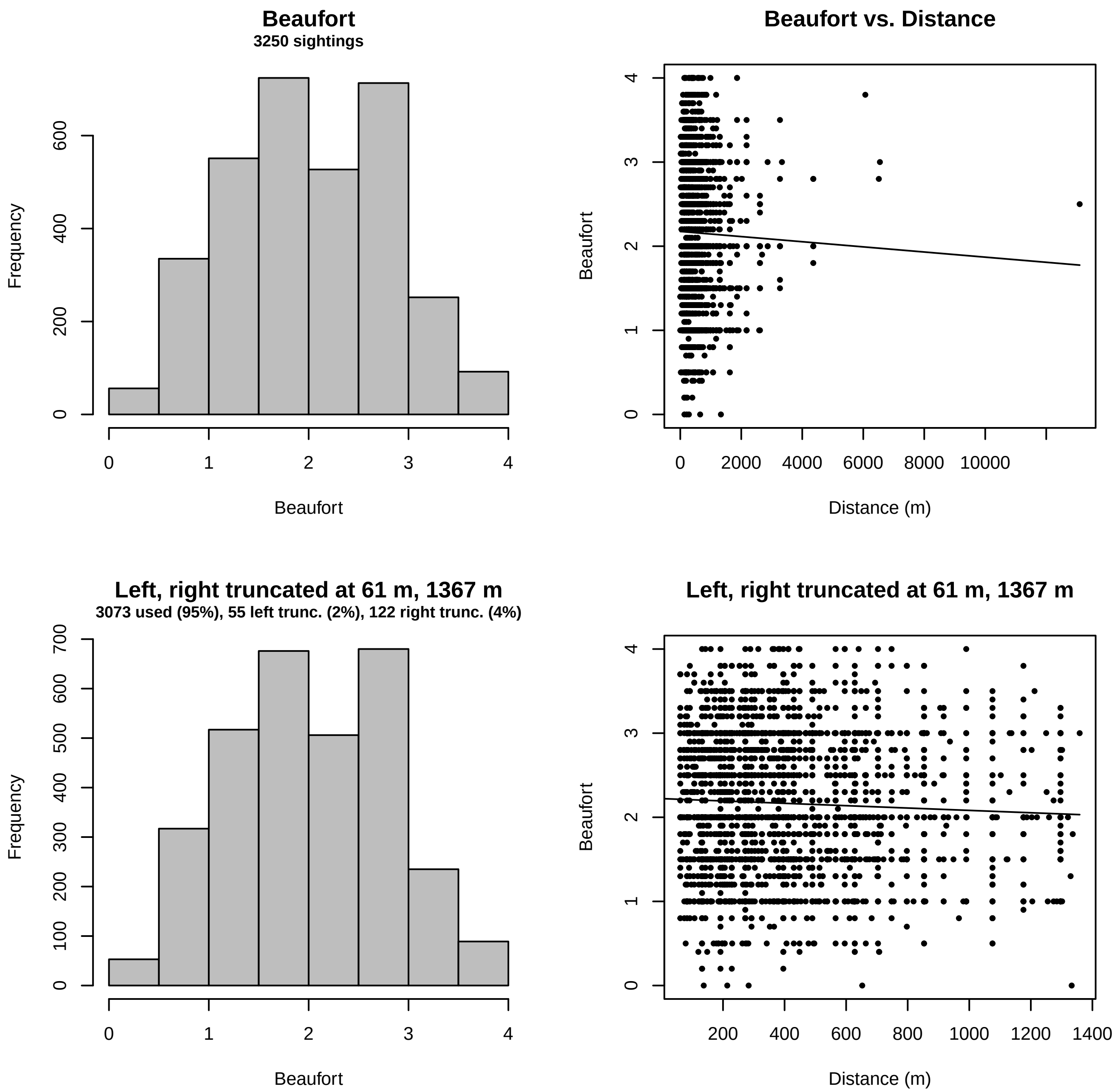


Figure 35: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the NARWSS 2003-2016 detection function.

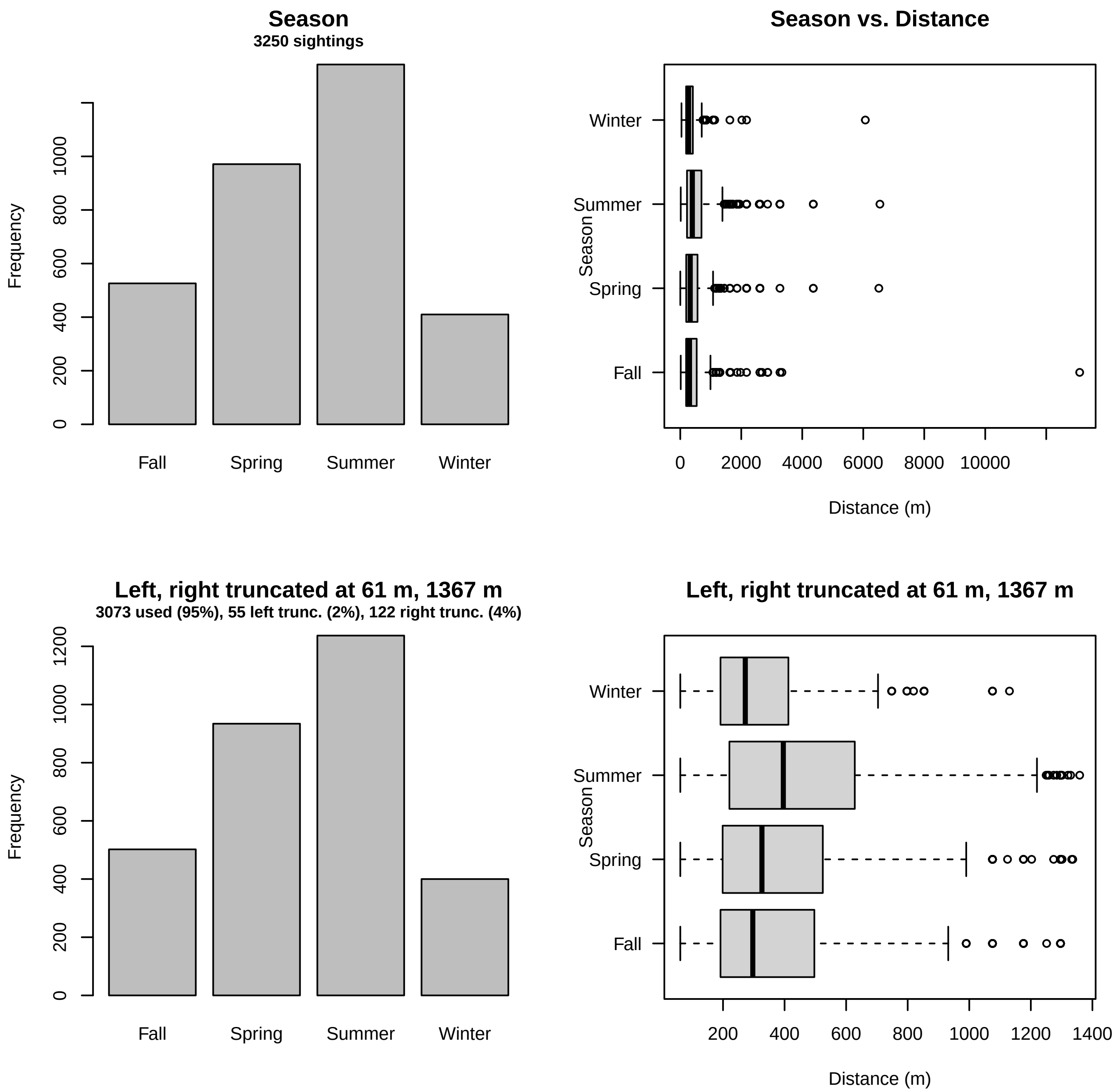


Figure 36: Distribution of the Season covariate before (top row) and after (bottom row) observations were truncated to fit the NARWSS 2003-2016 detection function.

3.2.1.5 UNCW Navy Surveys

After right-truncating observations greater than 1600 m, we fitted the detection function to the 1523 observations that remained (Table 15). The selected detection function (Figure 37) used a half normal key function with Glare (Figure 38) and Visibility (Figure 39) as covariates.

Table 15: Observations used to fit the UNCW Navy Surveys detection function.

ScientificName	n
Delphinus delphis	77
Lagenodelphis hosei	1
Stenella attenuata	2
Stenella clymene	11
Stenella coeruleoalba	19
Stenella frontalis	480
Stenella longirostris	1
Steno bredanensis	14
Tursiops truncatus	918
Total	**1523**

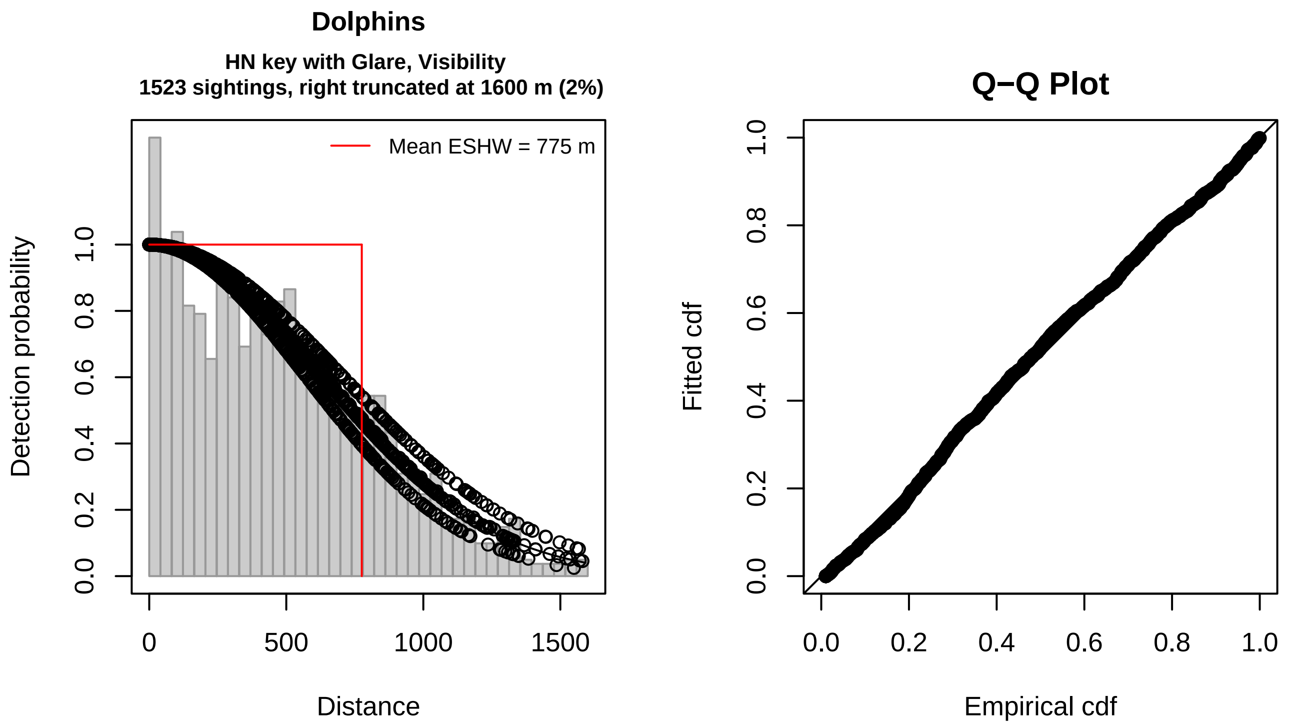


Figure 37: UNCW Navy Surveys detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  1523
Distance range         :  0  -  1600
AIC                    :  21665.78

Detection function:
 Half-normal key function

Detection function parameters
Scale coefficient(s):
                          estimate         se
(Intercept)             6.55223233 0.04798577
GlareNone, 0-25%, Unk. -0.10934970 0.05247015
VisibilityHalf         -0.09759271 0.04601702
```

```
                         Estimate          SE         CV
Average p               0.4827398  0.01003395 0.02078542
N in covered region 3154.9084328 87.71221948 0.02780183

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.331909  p = 0.110182
```

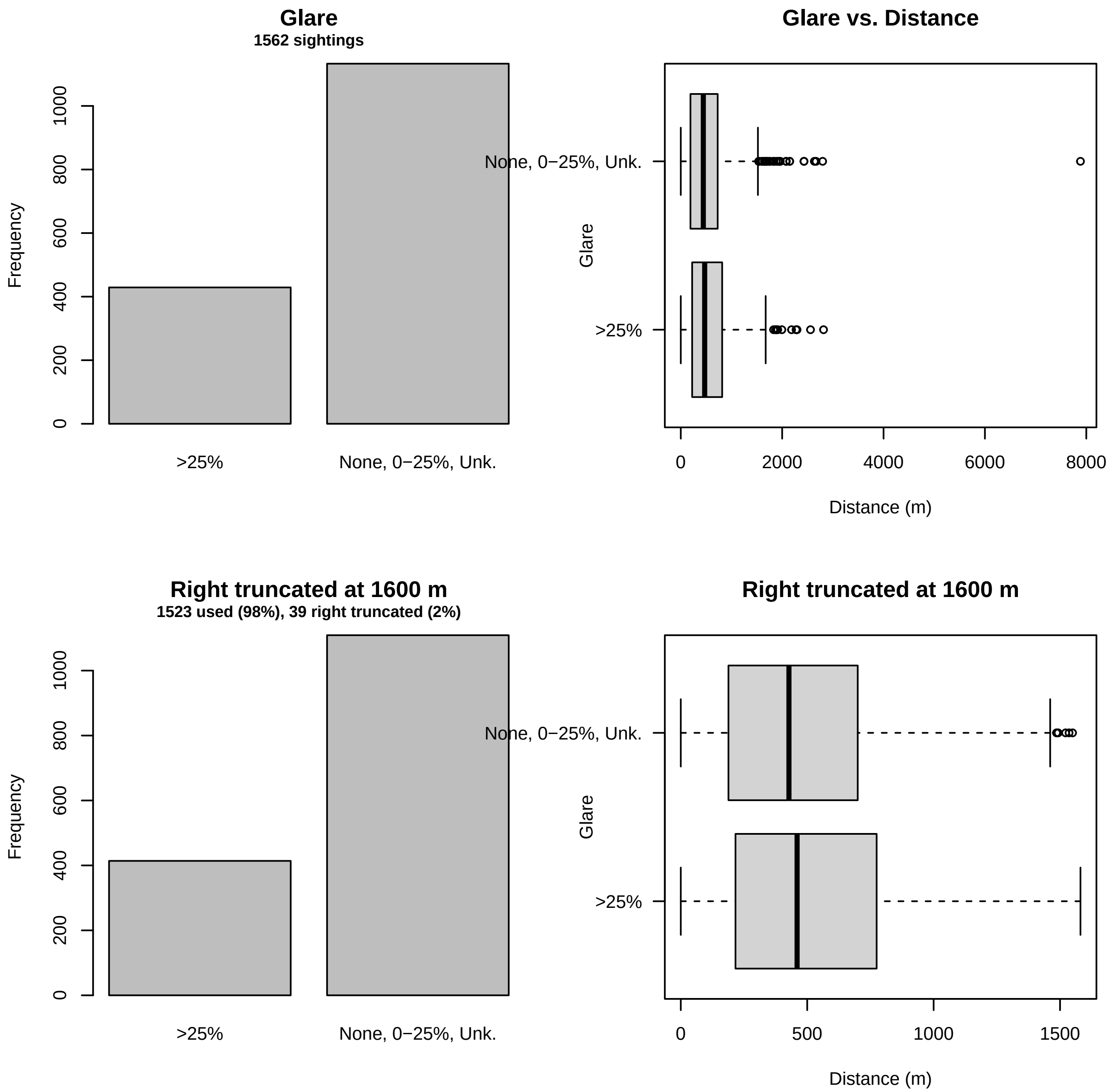


Figure 38: Distribution of the Glare covariate before (top row) and after (bottom row) observations were truncated to fit the UNCW Navy Surveys detection function.

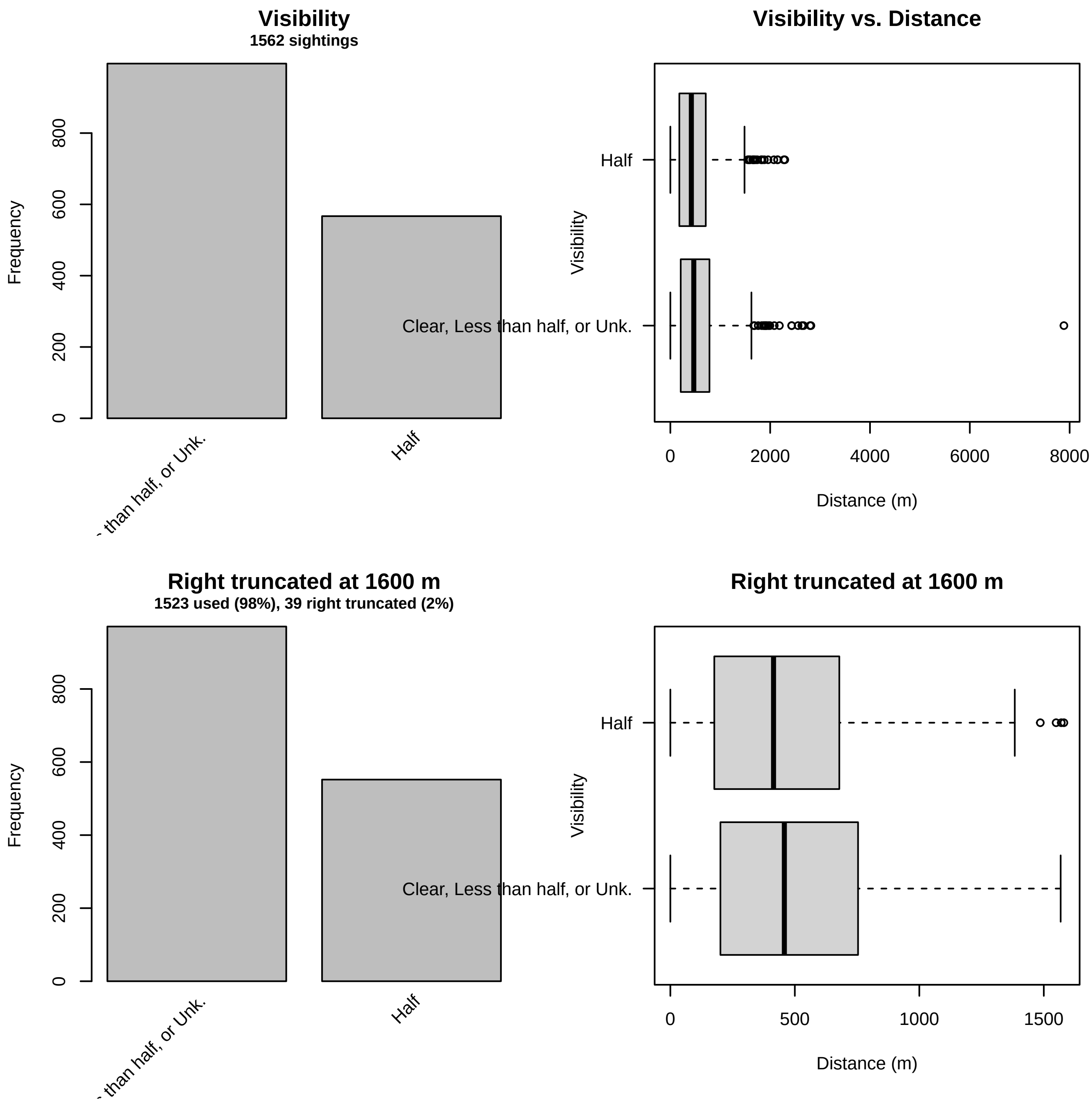


Figure 39: Distribution of the Visibility covariate before (top row) and after (bottom row) observations were truncated to fit the UNCW Navy Surveys detection function.

3.2.1.6 UNCW Right Whale Surveys

After right-truncating observations greater than 528 m and left-truncating observations less than 54 m (Figure 41), we fitted the detection function to the 1821 observations that remained (Table 16). The selected detection function (Figure 40) used a hazard rate key function with no covariates.

Table 16: Observations used to fit the UNCW Right Whale Surveys detection function.

ScientificName	n
Delphinus delphis	26
Stenella frontalis	4
Tursiops truncatus	1791
Total	**1821**

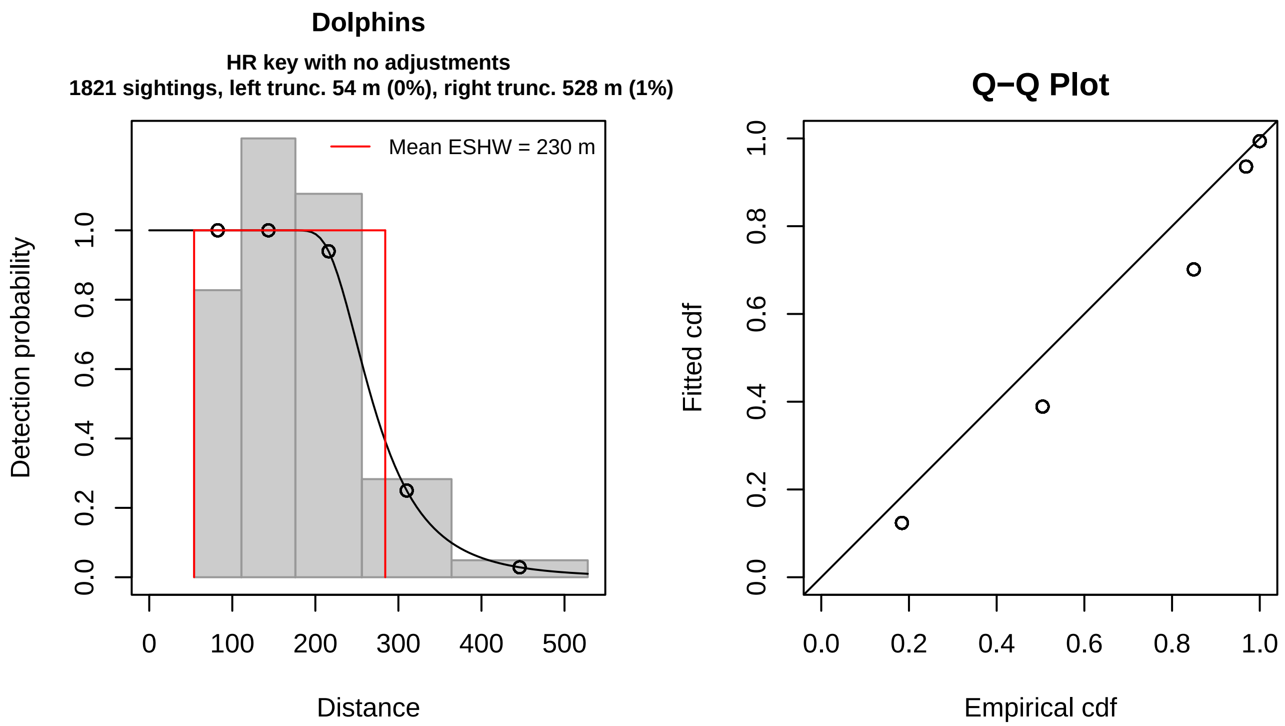


Figure 40: UNCW Right Whale Surveys detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  1821
Distance range         :  54  -  528
AIC                    :  5176.116

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
            estimate         se
(Intercept) 5.538954 0.02098751

Shape coefficient(s):
            estimate         se
(Intercept) 1.841299 0.06464608

                        Estimate          SE         CV
Average p              0.4855453  0.009233858 0.01901750
N in covered region 3750.4226341 95.188173832 0.02538065
```

```
Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 14.468539  p = 0.010416
```

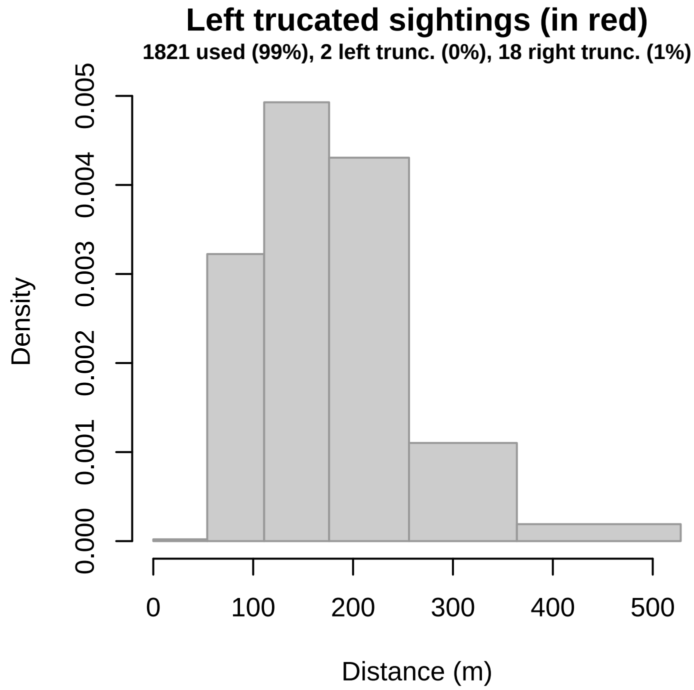


Figure 41: Density histogram of observations used to fit the UNCW Right Whale Surveys detection function, with the left-most bar showing observations at distances less than 54 m, which were left-truncated and excluded from the analysis [Buckland et al. (2001)]. (This bar may be very short if there were very few left-truncated sightings, or very narrow if the left truncation distance was very small; in either case it may not appear red.)

3.2.1.7 UNCW Early Surveys

After right-truncating observations greater than 333 m and left-truncating observations less than 14 m (Figure 43), we fitted the detection function to the 349 observations that remained (Table 17). The selected detection function (Figure 42) used a half normal key function with Beaufort (Figure 44) as a covariate.

Table 17: Observations used to fit the UNCW Early Surveys detection function.

ScientificName	n
Delphinus delphis	5
Stenella frontalis	1
Tursiops truncatus	343
Total	**349**

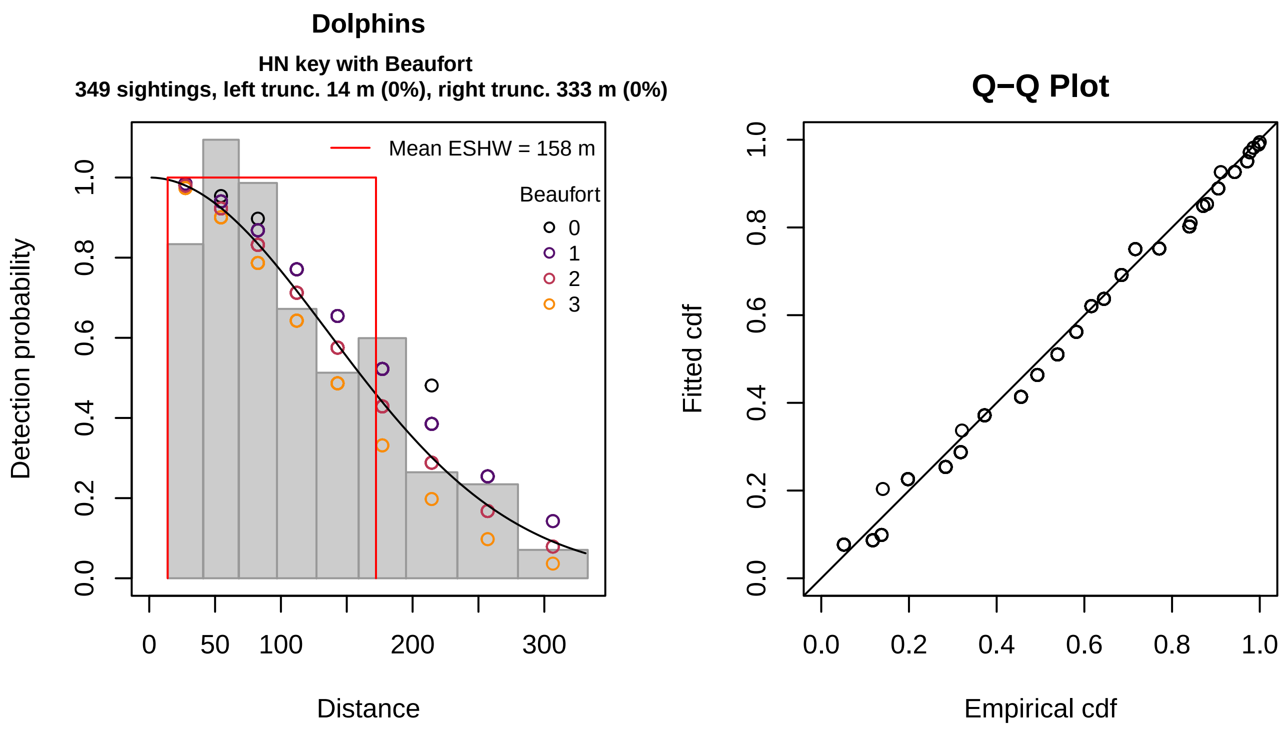


Figure 42: UNCW Early Surveys detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  349
Distance range         :  14  -  333
AIC                    :  1464.597

Detection function:
 Half-normal key function

Detection function parameters
Scale coefficient(s):
              estimate        se
(Intercept)  5.1778911 0.14575211
Beaufort    -0.1325498 0.07066838

                       Estimate          SE         CV
Average p             0.4915207  0.02352103 0.04785360
N in covered region 710.0413079 43.53534195 0.06131382

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.278162  p = 0.155953
```

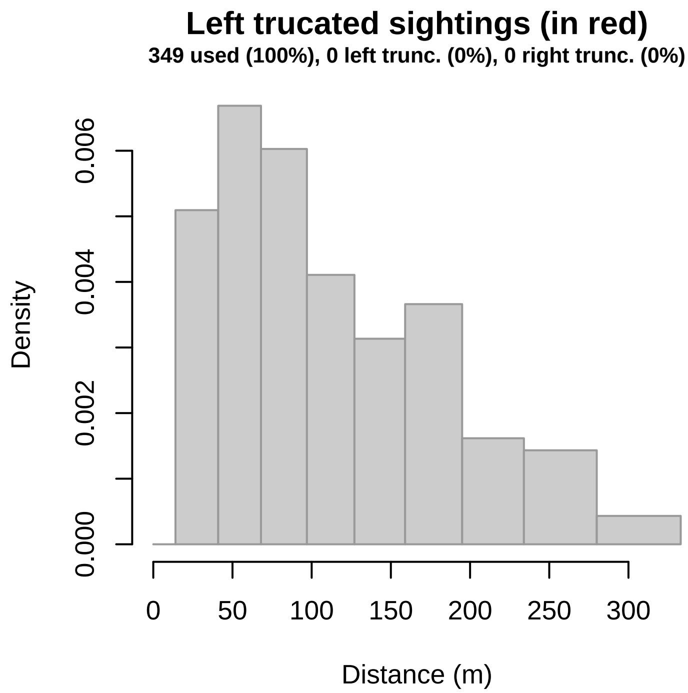


Figure 43: Density histogram of observations used to fit the UNCW Early Surveys detection function, with the left-most bar showing observations at distances less than 14 m, which were left-truncated and excluded from the analysis [Buckland et al. (2001)]. (This bar may be very short if there were very few left-truncated sightings, or very narrow if the left truncation distance was very small; in either case it may not appear red.)

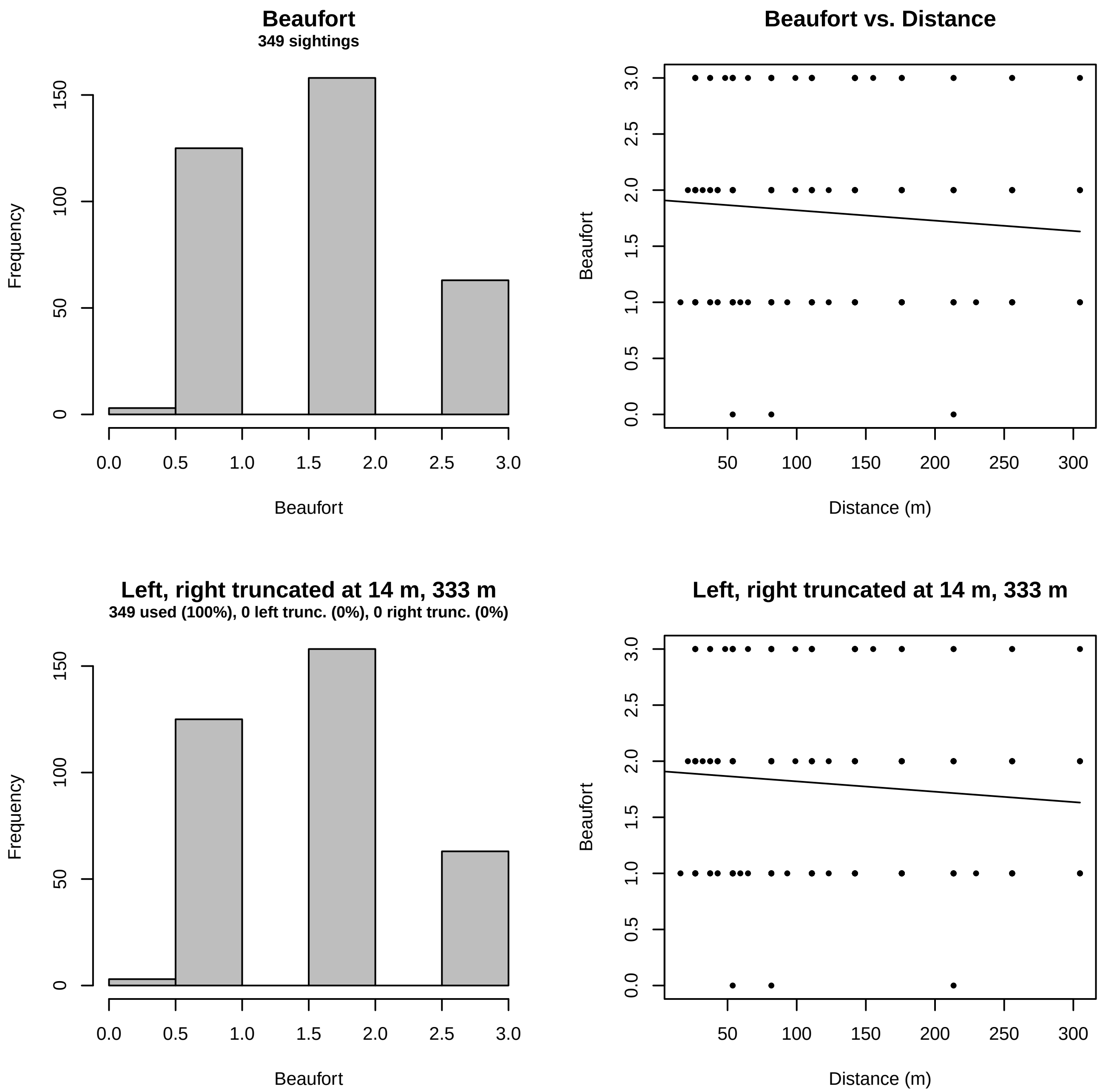


Figure 44: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the UNCW Early Surveys detection function.

3.2.1.8 VAMSC

After right-truncating observations greater than 1000 m, we fitted the detection function to the 303 observations that remained (Table 18). The selected detection function (Figure 45) used a hazard rate key function with no covariates.

Table 18: Observations used to fit the VAMSC detection function.

ScientificName	n
Delphinus delphis	30
Stenella frontalis	4
Tursiops truncatus	269
Total	**303**

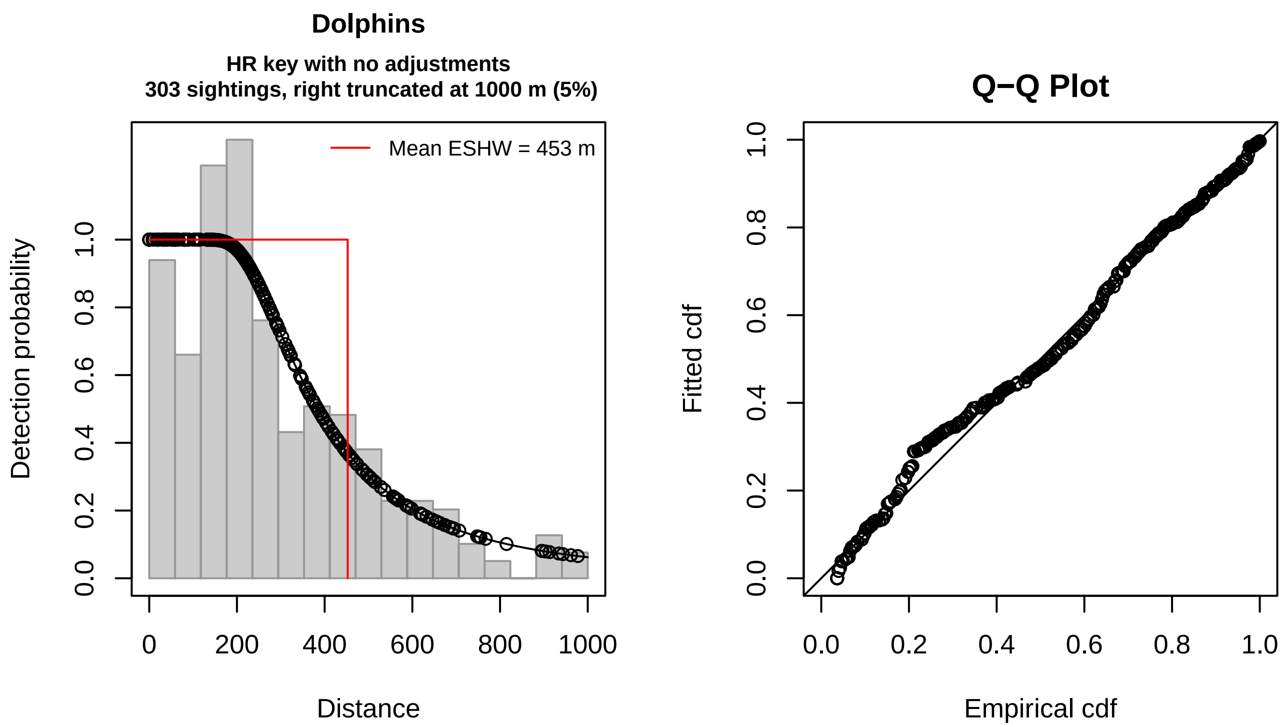


Figure 45: VAMSC detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  303
Distance range         :  0  -  1000
AIC                    :  3992.632

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
            estimate        se
(Intercept) 5.803823 0.1019737

Shape coefficient(s):
             estimate        se
(Intercept) 0.9119562 0.1438459

                        Estimate          SE         CV
Average p              0.4525805  0.02853931 0.06305908
N in covered region 669.4942067 50.91287837 0.07604678

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.212402  p = 0.244680
```

3.2.1.9 HDR

After right-truncating observations greater than 1500 m and left-truncating observations less than 111 m (Figure 47), we fitted the detection function to the 203 observations that remained (Table 19). The selected detection function (Figure 46) used a hazard rate key function with Season (Figure 48) and Swell (Figure 49) as covariates.

Table 19: Observations used to fit the HDR detection function.

ScientificName	n
Delphinus delphis	47
Stenella coeruleoalba	14
Stenella frontalis	19
Tursiops truncatus	123
Total	**203**

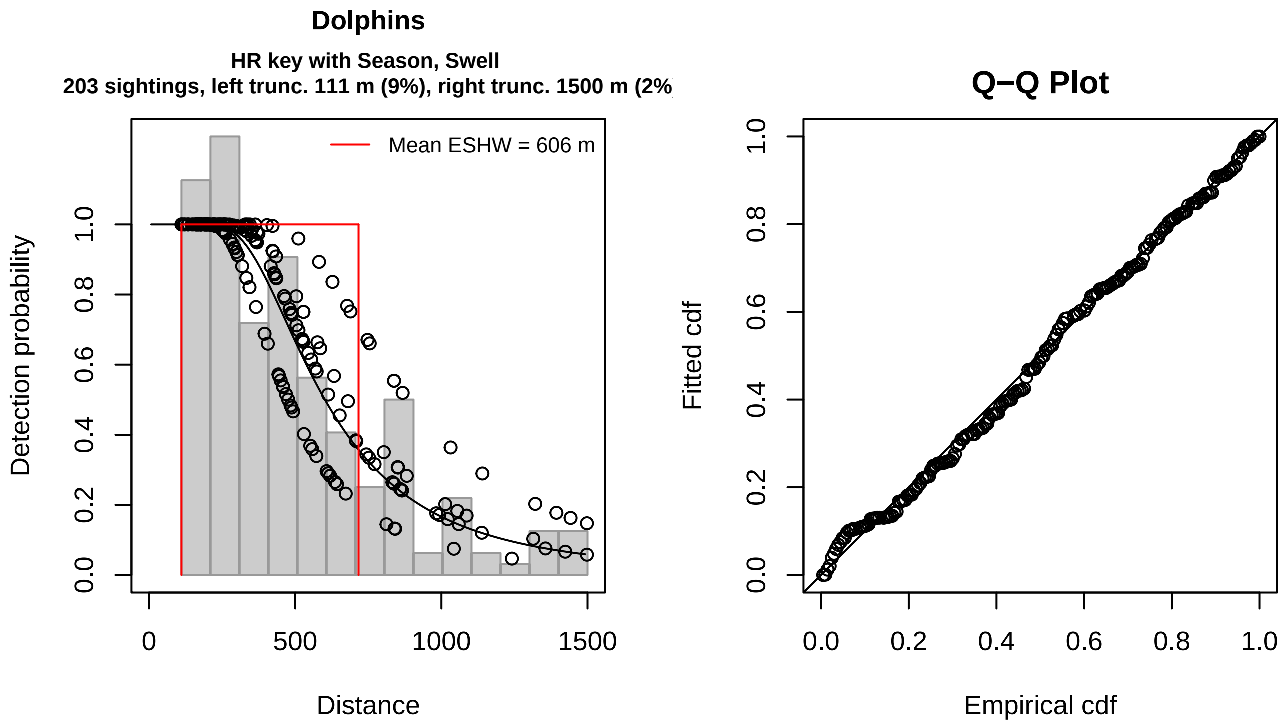


Figure 46: HDR detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  203
Distance range         :  111  -  1500
AIC                    :  2802.845

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
                      estimate        se
(Intercept)          6.3015171 0.1328018
SeasonWinter, Spring -0.2671651 0.1458664
Swell3-4             0.3527933 0.1530784

Shape coefficient(s):
            estimate        se
(Intercept) 1.026101 0.1620057

                      Estimate          SE          CV
```

```
Average p             0.419883  0.03654238 0.08702991
N in covered region 483.467993 49.56848062 0.10252691

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.059652  p = 0.816171
```

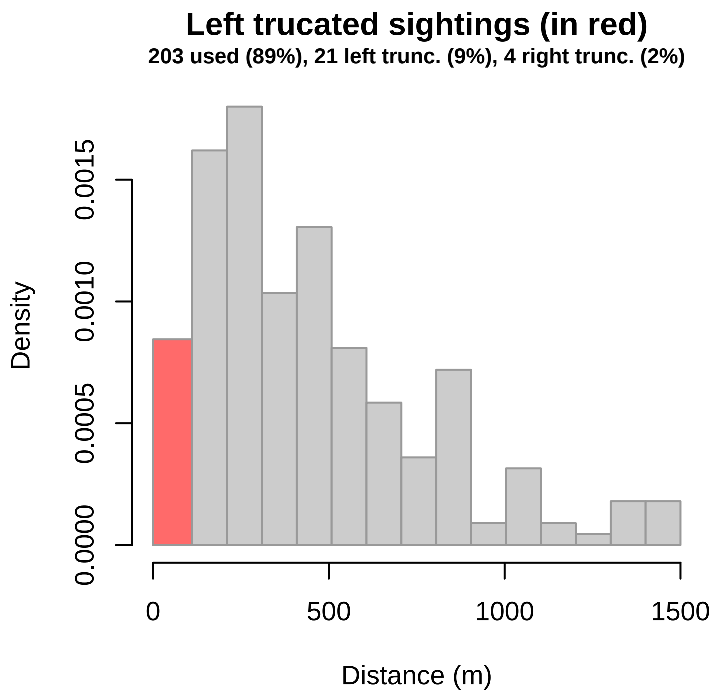


Figure 47: Density histogram of observations used to fit the HDR detection function, with the left-most bar showing observations at distances less than 111 m, which were left-truncated and excluded from the analysis [Buckland et al. (2001)]. (This bar may be very short if there were very few left-truncated sightings, or very narrow if the left truncation distance was very small; in either case it may not appear red.)

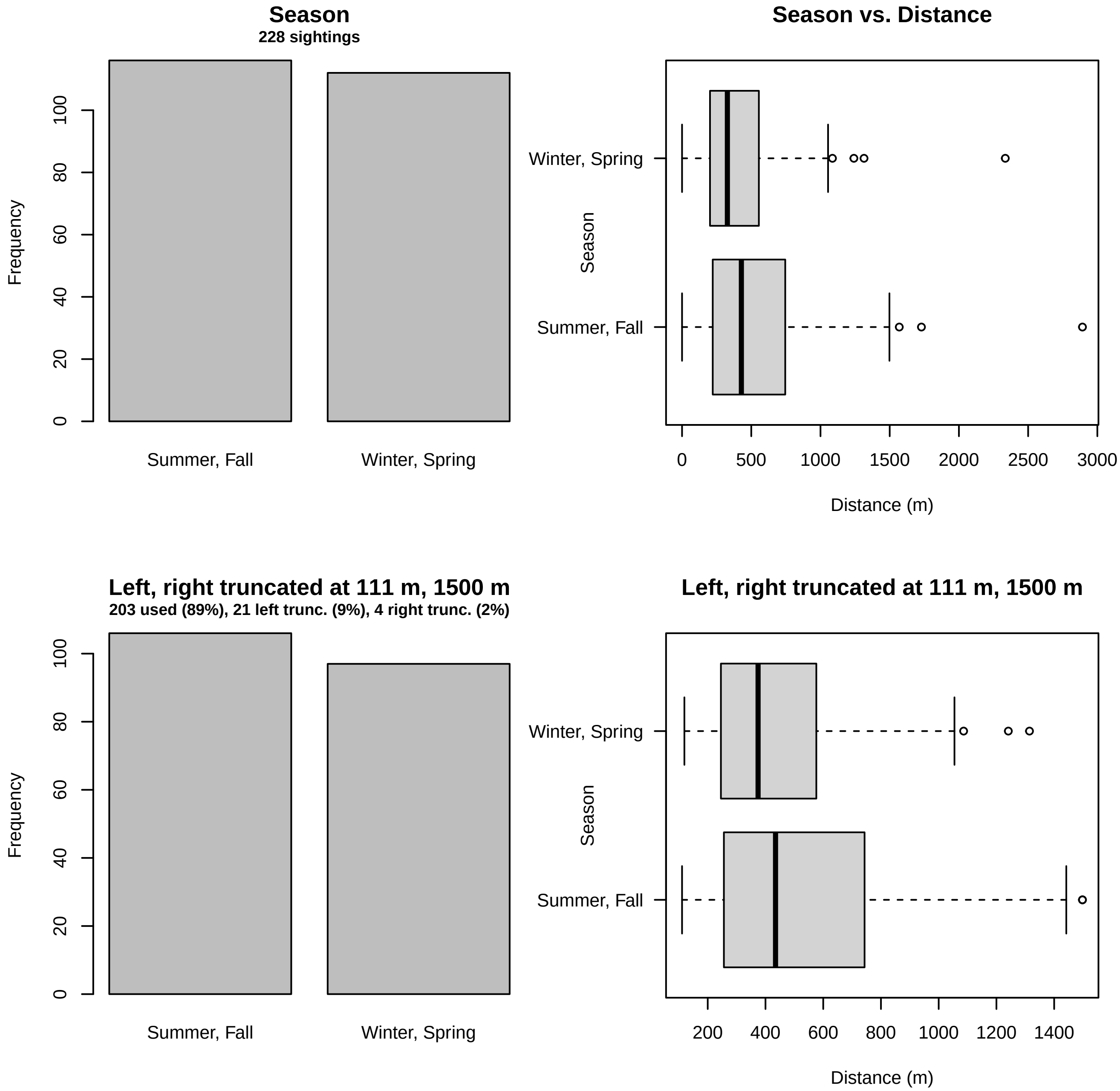


Figure 48: Distribution of the Season covariate before (top row) and after (bottom row) observations were truncated to fit the HDR detection function.

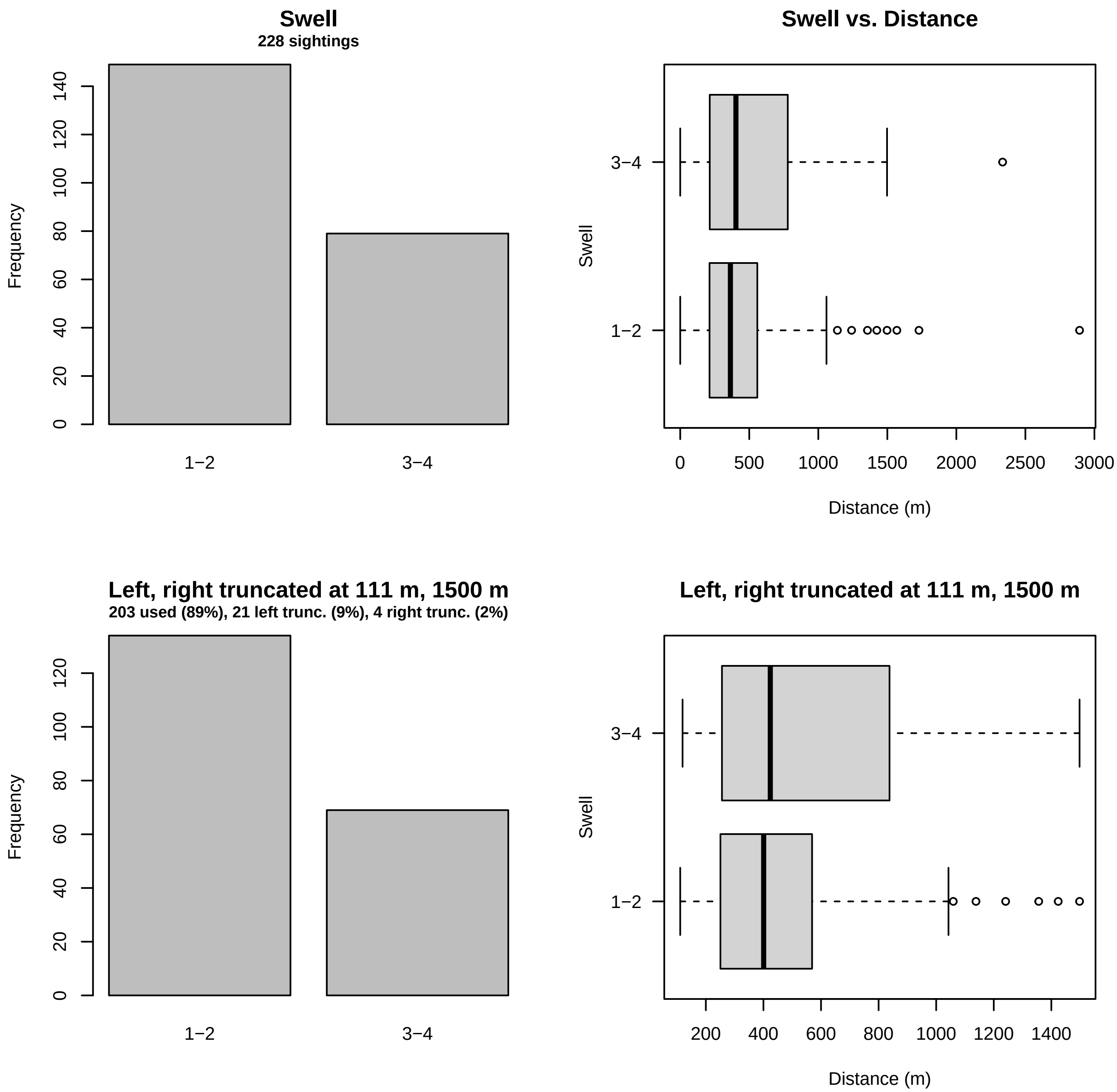


Figure 49: Distribution of the Swell covariate before (top row) and after (bottom row) observations were truncated to fit the HDR detection function.

3.2.2 Shipboard Surveys

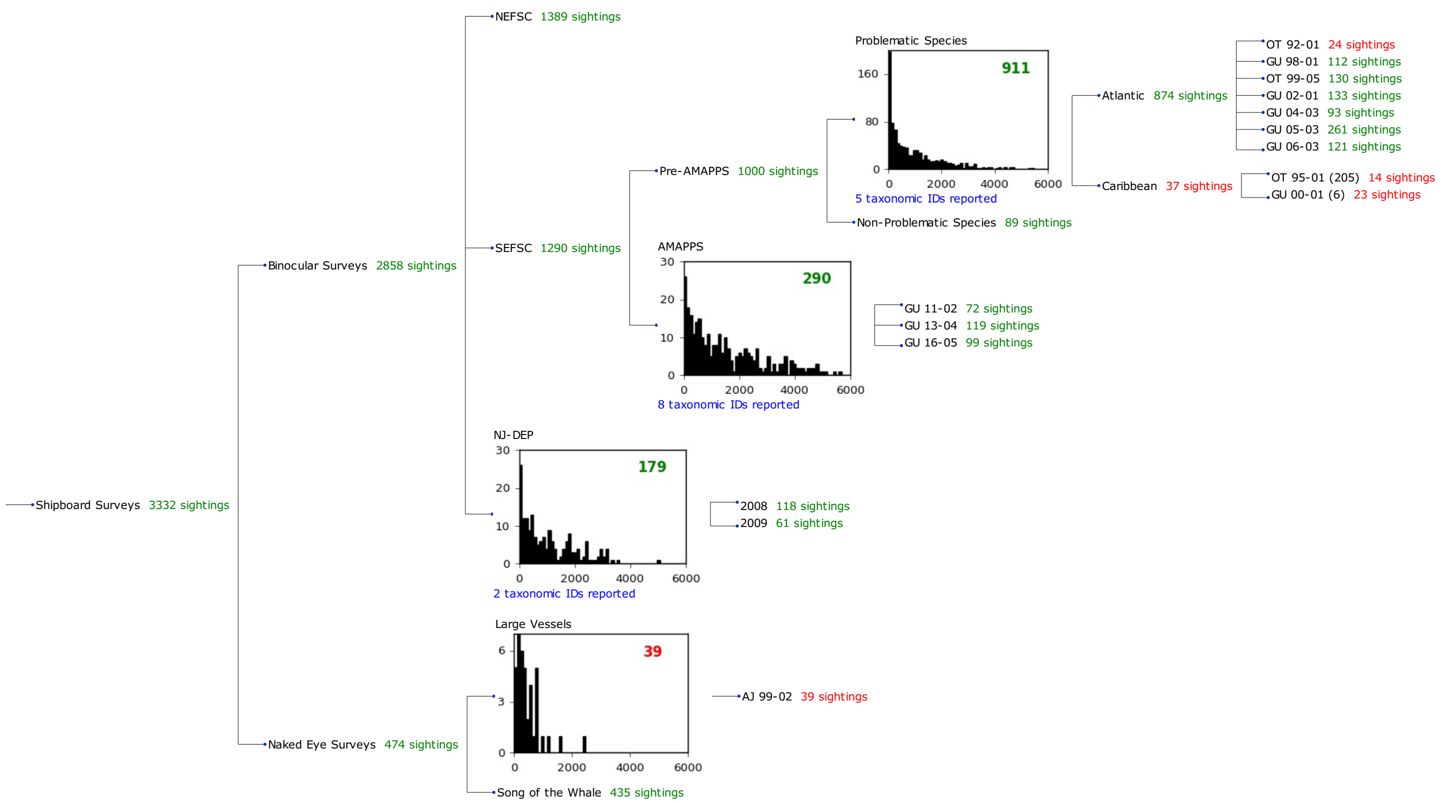


Figure 50: Detection hierarchy for shipboard surveys, showing how they were pooled during detectability modeling, for detection functions that pooled multiple taxa but could not use a taxonomic covariate to account for differences between them. Each histogram represents a detection function and summarizes the perpendicular distances of observations that were pooled to fit it, prior to truncation. Observation counts, also prior to truncation, are shown in green when they met the recommendation of Buckland et al. (2001) that detection functions utilize at least 60 sightings, and red otherwise. For rare taxa, it was not always possible to meet this recommendation, yielding higher statistical uncertainty. During the spatial modeling stage of the analysis, effective strip widths were computed for each survey using the closest detection function above it in the hierarchy (i.e. moving from right to left in the figure). Surveys that do not have a detection function above them in this figure were either addressed by a detection function presented in a different section of this report, or were omitted from the analysis.

3.2.2.1 SEFSC Pre-AMAPPS Problematic Species

After right-truncating observations greater than 4000 m and left-truncating observations less than 200 m (Figure 52), we fitted the detection function to the 616 observations that remained (Table 20). The selected detection function (Figure 51) used a hazard rate key function with Beaufort (Figure 53) and VesselName (Figure 54) as covariates.

Table 20: Observations used to fit the SEFSC Pre-AMAPPS Problematic Species detection function.

ScientificName	n
Delphinus delphis	34
Stenella attenuata	14
Stenella frontalis	262
Steno bredanensis	4
Tursiops truncatus	302
Total	**616**

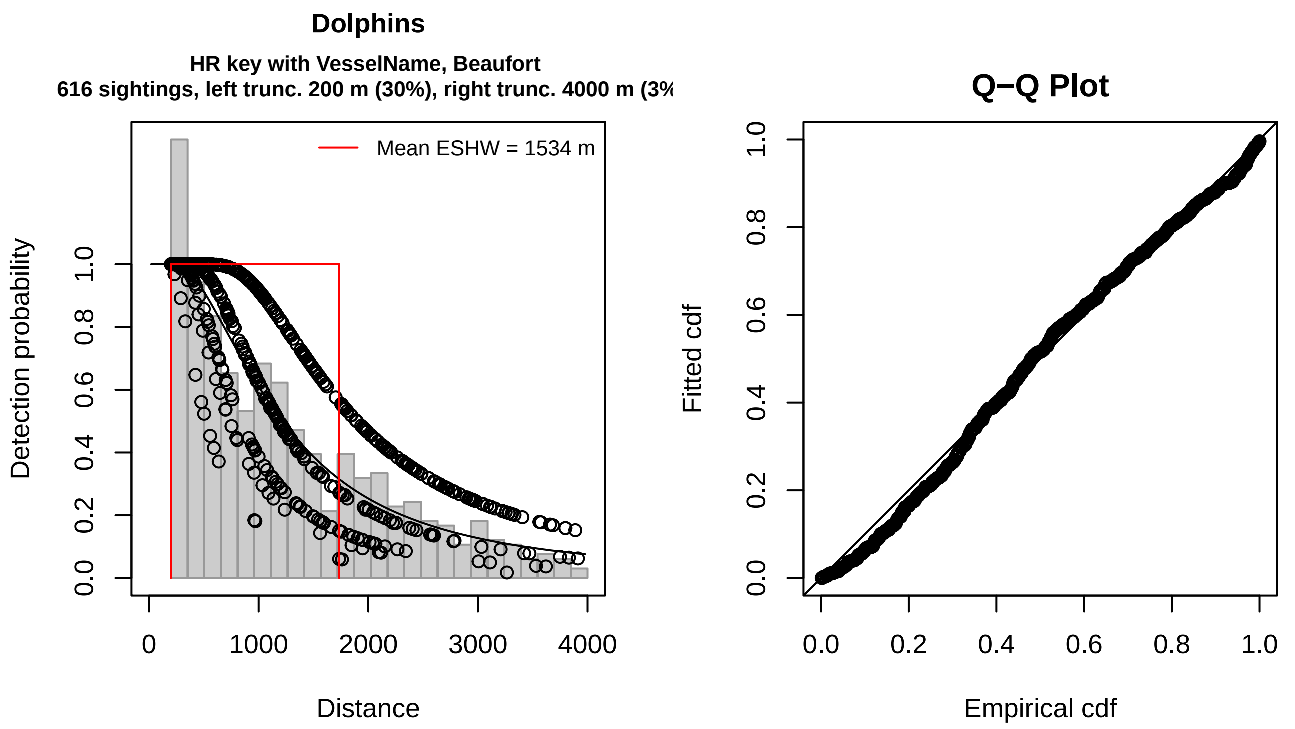


Figure 51: SEFSC Pre-AMAPPS Problematic Species detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  616
Distance range         :  200  -  4000
AIC                    :  9753.004

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
                      estimate         se
(Intercept)          7.3628462 0.09422017
VesselNameOregon II -0.4793018 0.17480366
Beaufort3           -0.4668391 0.14302976
Beaufort4-5         -0.8137669 0.16103824

Shape coefficient(s):
            estimate         se
(Intercept) 0.689867 0.09372714

                        Estimate           SE         CV
Average p              0.3555714   0.02671315 0.07512737
N in covered region 1732.4228173 142.52885613 0.08227140

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.313292  p = 0.124062
```

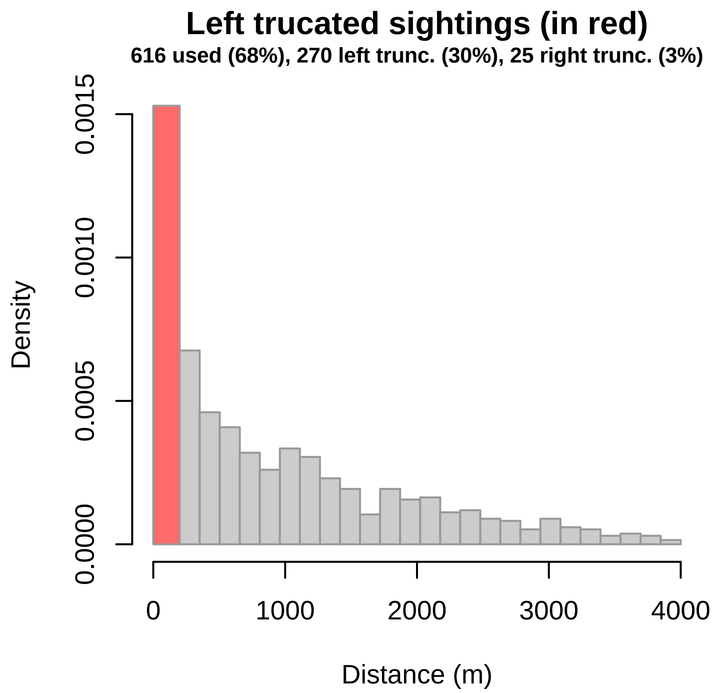


Figure 52: Density histogram of observations used to fit the SEFSC Pre-AMAPPS Problematic Species detection function, with the left-most bar showing observations at distances less than 200 m, which were left-truncated and not used to fit the detection function. (This bar may be very short if there were very few left-truncated sightings, or very narrow if the left truncation distance was very small; in either case it may not appear red.) These were excluded because they formed a problematic "spike" in detections close to the trackline, suggesting that animals approached the vessel (e.g. to bow-ride) prior to being detected. To address this, we fitted the detection function to the observations beyond the spike and assumed that within it, detection probability was 1, effectively treating it like a strip transect. We then added the left-truncated observations back into the analysis as if they occurred in this strip. This treatment may have resulted in an underestimation of detection probability.

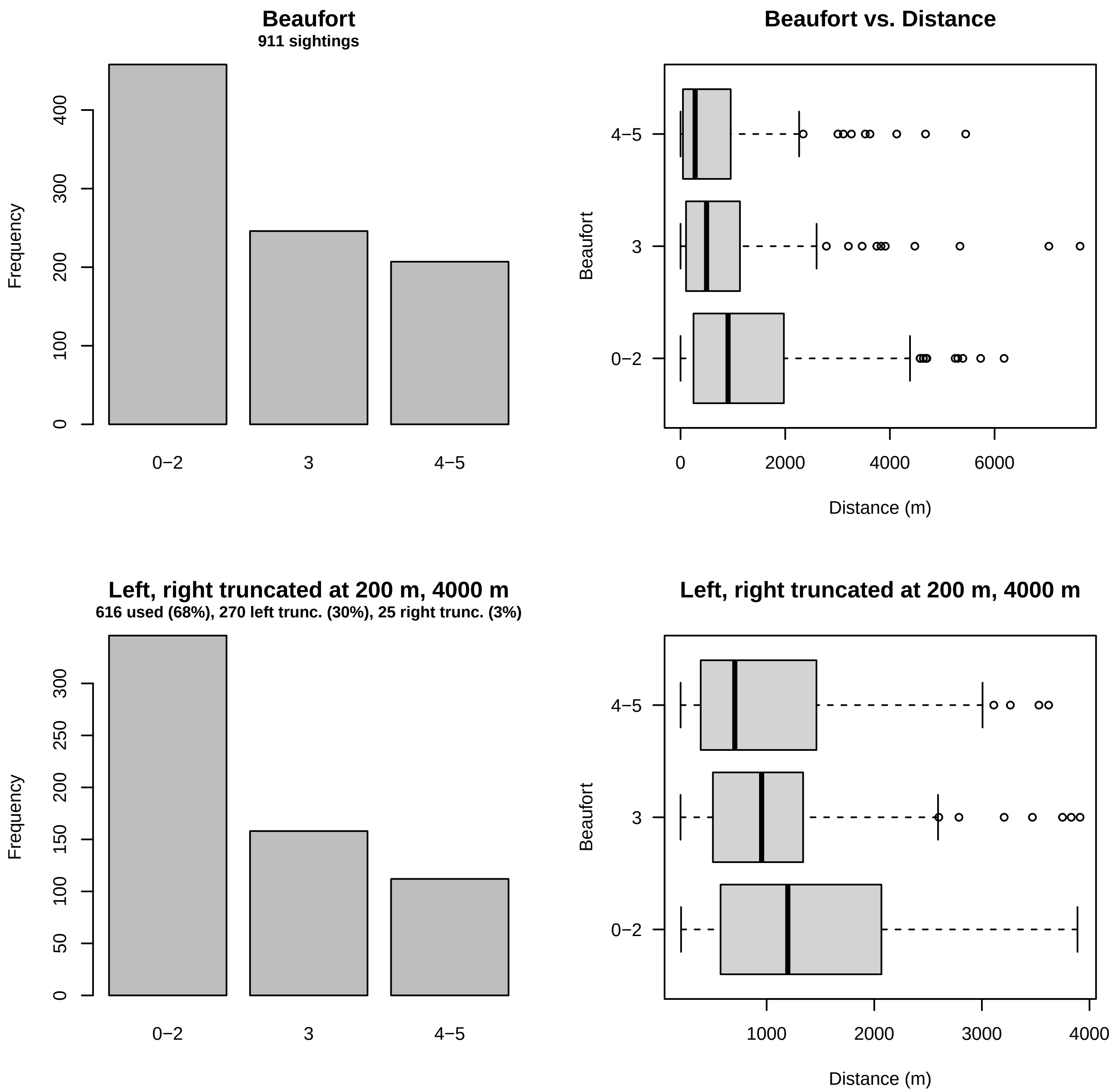


Figure 53: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the SEFSC Pre-AMAPPS Problematic Species detection function.

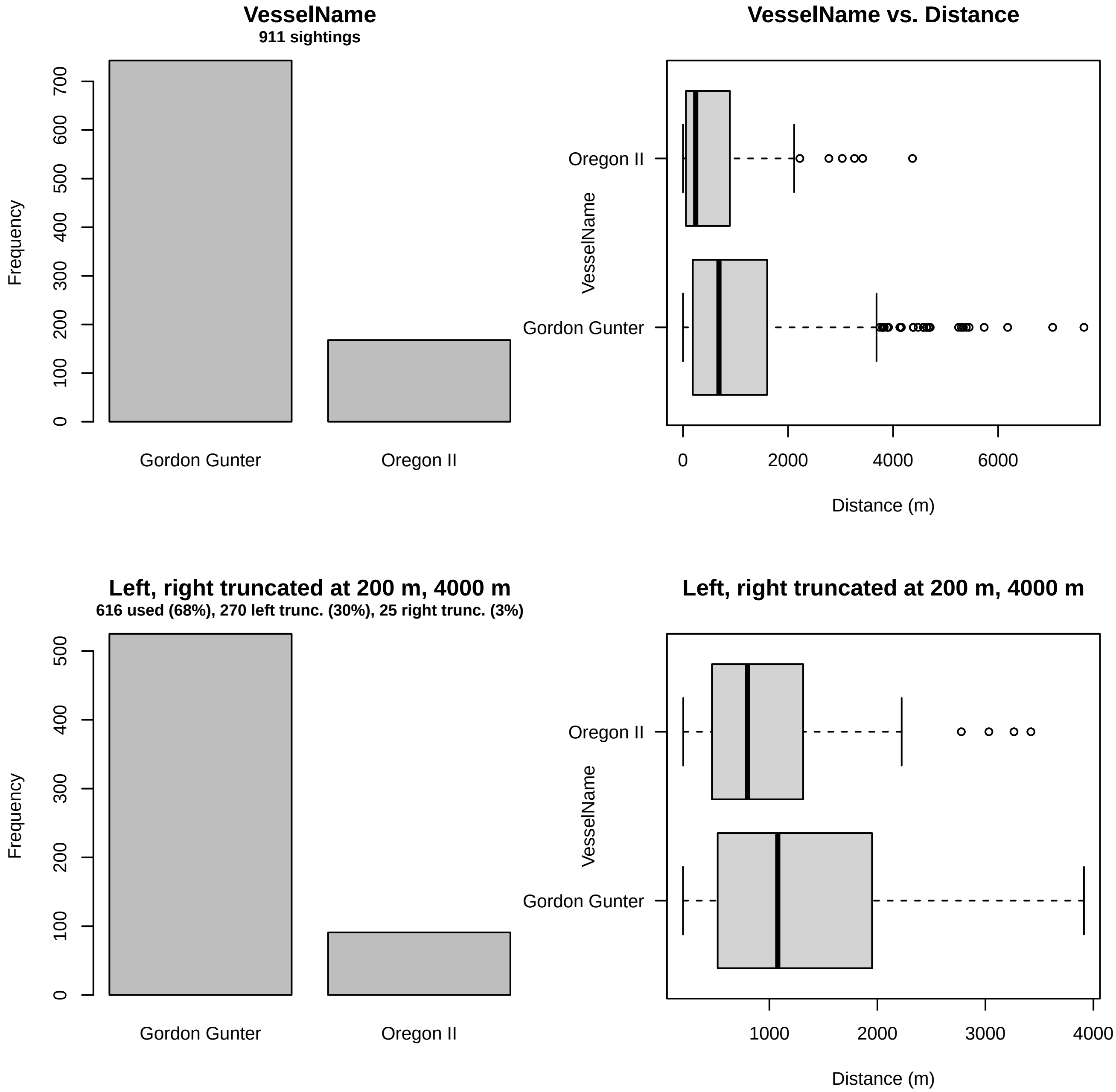


Figure 54: Distribution of the VesselName covariate before (top row) and after (bottom row) observations were truncated to fit the SEFSC Pre-AMAPPS Problematic Species detection function.

3.2.2.2 SEFSC AMAPPS

After right-truncating observations greater than 5000 m, we fitted the detection function to the 284 observations that remained (Table 21). The selected detection function (Figure 55) used a hazard rate key function with Beaufort (Figure 56) as a covariate.

Table 21: Observations used to fit the SEFSC AMAPPS detection function.

ScientificName	n
Delphinus delphis	2
Stenella attenuata	10
Stenella clymene	3
Stenella coeruleoalba	11
Stenella frontalis	84
Stenella longirostris	1
Steno bredanensis	2
Tursiops truncatus	171
Total	**284**

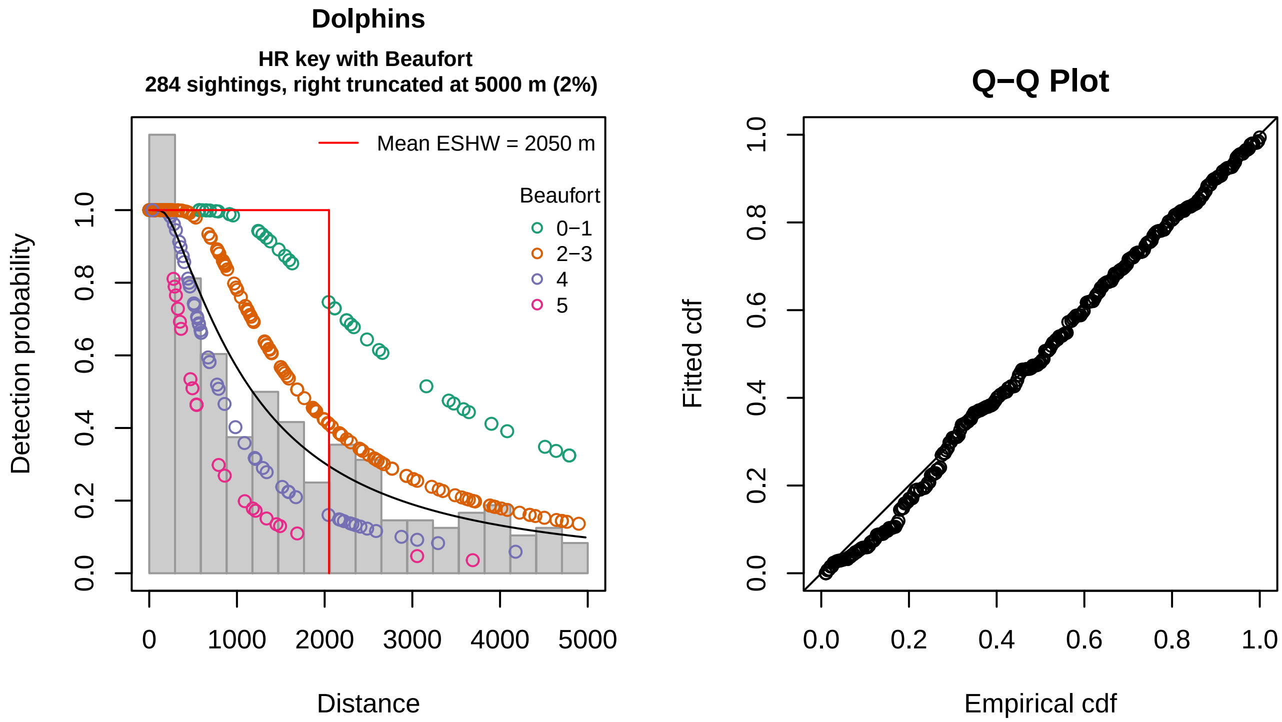


Figure 55: SEFSC AMAPPS detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  284
Distance range         :  0  -  5000
AIC                    :  4678.464

Detection function:
 Hazard-rate key function

Detection function parameters
Scale coefficient(s):
              estimate        se
(Intercept)  7.8386611 0.3487749
Beaufort2-3 -0.6450433 0.3816484
Beaufort4   -1.3990617 0.4441169
Beaufort5   -1.8689041 0.5186901
```

```
Shape coefficient(s):
             estimate        se
(Intercept) 0.3878689 0.1380351

                        Estimate          SE        CV
Average p              0.3478259   0.03965009 0.1139941
N in covered region 816.5004271 101.68622285 0.1245391

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.107898  p = 0.547527
```

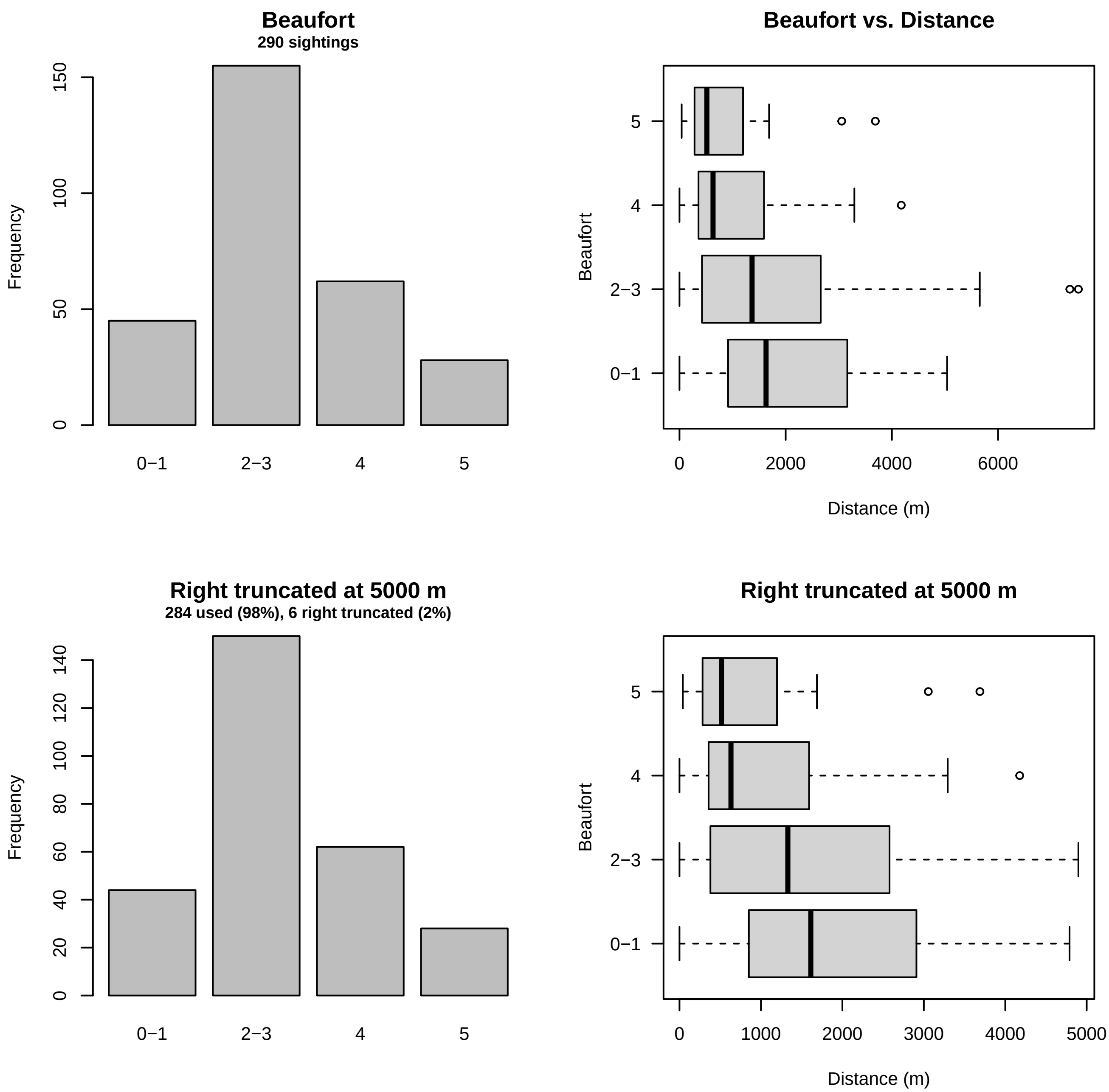


Figure 56: Distribution of the Beaufort covariate before (top row) and after (bottom row) observations were truncated to fit the SEFSC AMAPPS detection function.

3.2.2.3 NJ-DEP

After right-truncating observations greater than 3200 m, we fitted the detection function to the 175 observations that remained (Table 22). The selected detection function (Figure 57) used a hazard rate key function with no covariates.

Table 22: Observations used to fit the NJ-DEP detection function.

ScientificName	n
Delphinus delphis	19
Tursiops truncatus	156
Total	**175**

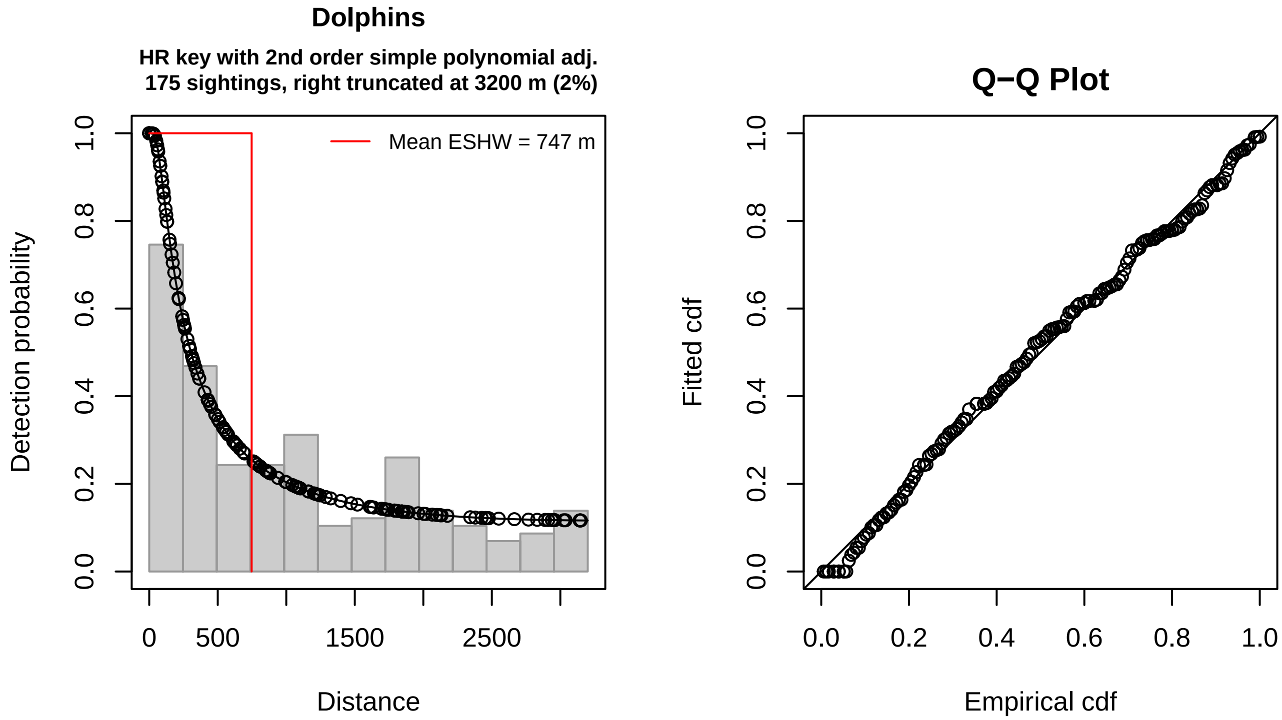


Figure 57: NJ-DEP detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  175
Distance range         :  0  -  3200
AIC                    :  2750.547

Detection function:
 Hazard-rate key function with simple polynomial adjustment term of order 2

Detection function parameters
Scale coefficient(s):
            estimate       se
(Intercept) 5.340225 0.502875

Shape coefficient(s):
                estimate        se
(Intercept) 2.663565e-07 0.3025183
```

```
Adjustment term coefficient(s):
                 estimate       se
poly, order 2 0.8448098 1.306568


Monotonicity constraints were enforced.
                         Estimate           SE        CV
Average p              0.2335197   0.05159473 0.2209438
N in covered region 749.4013460 172.84391894 0.2306427

Monotonicity constraints were enforced.

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.069450  p = 0.754942
```

3.2.2.4 Large Vessels

After right-truncating observations greater than 1100 m, we fitted the detection function to the 36 observations that remained (Table 23). The selected detection function (Figure 58) used a half normal key function with no covariates.

Table 23: Observations used to fit the Large Vessels detection function.

ScientificName	n
Lagenorhynchus acutus	36
Total	**36**

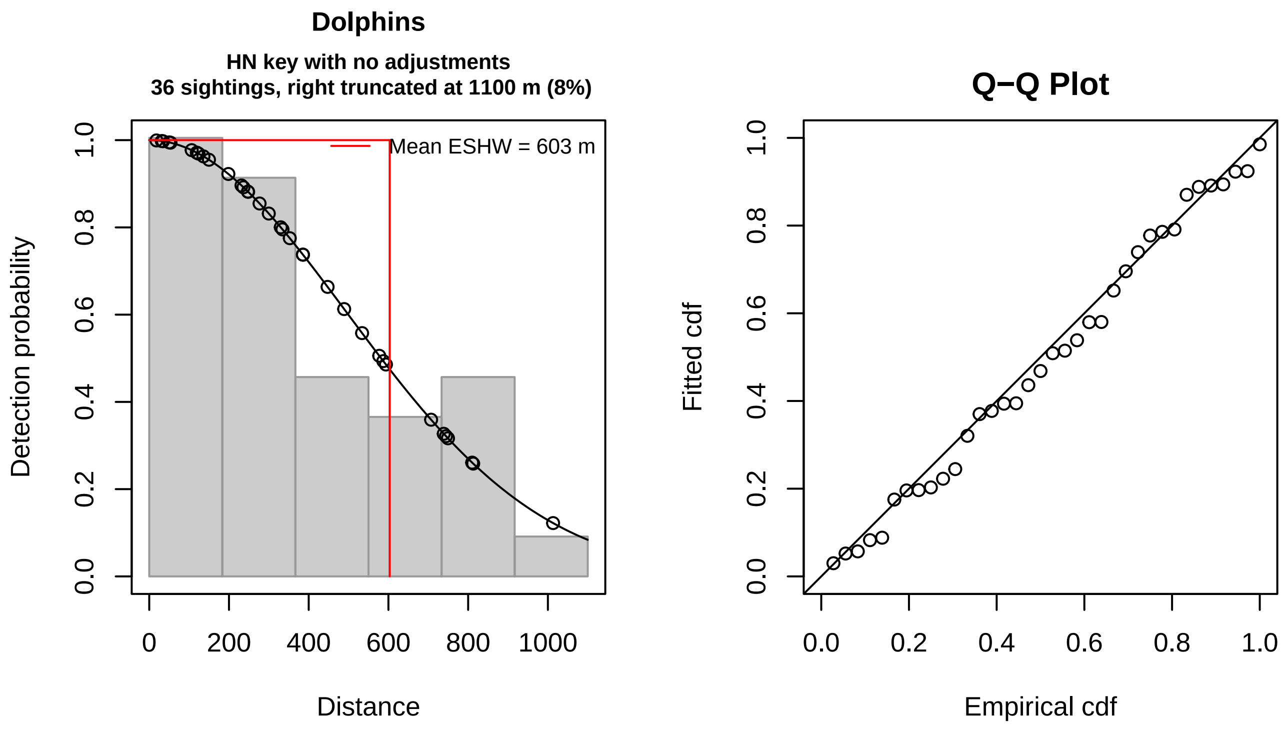


Figure 58: Large Vessels detection function and Q-Q plot showing its goodness of fit.

Statistical output for this detection function:

```
Summary for ds object
Number of observations :  36
Distance range         :  0  -  1100
```

```
AIC                   :  493.4472

Detection function:
 Half-normal key function

Detection function parameters
Scale coefficient(s):
            estimate        se
(Intercept) 6.202683 0.1646341

                     Estimate          SE        CV
Average p           0.5483057  0.07646146 0.1394504
N in covered region 65.6568085 11.74385160 0.1788672

Distance sampling Cramer-von Mises test (unweighted)
Test statistic = 0.026241  p = 0.986825
```

4 Bias Corrections

Density surface modeling methodology uses *distance sampling* (Buckland et al. 2001) to model the probability that an observer on a line transect survey will detect an animal given the perpendicular distance to it from the transect line. Distance sampling assumes that detection probability is 1 when perpendicular distance is 0. When this assumption is not met, detection probability is biased high, leading to an underestimation of density and abundance. This is known as the $g_0 < 1$ problem, where g_0 refers to the detection probability at distance 0. Modelers often try to address this problem by estimating g_0 empirically and dividing it into estimated density or abundance, thereby correcting those estimates to account for the animals that were presumed missed.

Two important sources of bias for visual surveys are known as *availability bias*, in which an animal was present on the transect line but impossible to detect, e.g. because it was under water, and *perception bias*, in which an animal was present and available but not noticed, e.g. because of its small size or cryptic coloration or behavior (Marsh and Sinclair 1989). Modelers often estimate the influence of these two sources of bias on detection probability independently, yielding two estimates of g_0, hereafter referred to as g_{0A} and g_{0P}, and multiply them together to obtain a final, combined estimate: $g_0 = g_{0A} \cdot g_{0P}$.

Our overall approach was to perform this correction on a per-observation basis, to have the flexibility to account for many factors such as platform type, surveyor institution, group size, group composition (e.g. singleton, mother-calf pair, or surface active group), and geographic location (e.g. feeding grounds vs. calving grounds). The level of complexity of the corrections varied by species according to the amount of information available, with North Atlantic right whale having the most elaborate corrections, derived from a substantial set of publications documenting its behavior, and various lesser known odontocetes having corrections based only on platform type (aerial or shipboard), derived from comparatively sparse information. Here we document the corrections used for Atlantic spotted dolphin.

4.1 Aerial Surveys

Reflecting the southerly distribution of the species, many sightings were reported by NOAA SEFSC during the AMAPPS aerial program but none by NOAA NEFSC (Table 1). Palka et al. (2021) developed perception bias corrections for SEFSC's AMAPPS aerial program using two team, mark recapture distance sampling (MRDS) methodology (Burt et al. 2014) for surveys conducted in 2010-2017. This was the only extant perception bias estimates developed from aerial surveys used in our analysis, aside from estimates developed earlier by Palka et al. (2017), which utilized an subset of the sightings used in their 2021 analysis, so we applied the Palka et al. (2021) estimates to all aerial survey programs (Table 24).

For all aerial surveys, to account for the influence of large group sizes on perception bias, we followed Carretta et al. (2000) and set the perception bias correction factor for sightings of more than 25 animals to $g_{0P} = 0.994$. Roughly 81% of SEFSC's sightings were of 25 animals or less.

We caution that it is possible that perception bias was different on the other aerial programs, as they often used different aircraft, flew at different altitudes, and were staffed by different personnel. Of particular concern are that many programs flew Cessna 337 Skymasters, which had flat windows, while NOAA flew de Havilland Twin Otters, which had bubble windows, which likely afforded a better view of the transect line and therefore might have required less of a correction than the Skymasters. Correcting the other programs using NOAA's estimate as we have done is likely to yield less bias than leaving them uncorrected, but we urge all programs to undertake their own efforts to estimate perception bias, as resources allow.

We estimated availability bias corrections using the Laake et al. (1997) estimator, which requires the use of dive and surface intervals. Few such data existed for Atlantic spotted dolphin in the literature. The best we could find were from Davis et al. (1996), who summarized the behavior of a single rehabilitated, VHF-tagged animal during the first 52 minutes after its release from rehabilitation. They reported relatively short intervals consistent with a short- and shallow-diving delphinid (Table 25). They went on to summarize over 15,000 dives recorded by satellite tag over the following three weeks, and reported that 93.3% of the dives were less than 2 minutes in duration, and the dolphin spent 95.9% of its time at depths less than 30 meters. More recently, measurements of myoglobin concentrations in muscle tissue (Arregui et al. 2021) and morphometric analysis of the aortic wall (Mompeó et al. 2020) concurred with the view that Atlantic spotted dolphins are shallower divers than short-beaked common dolphins or striped dolphins. Given that, we are comfortable utilizing the intervals reported by Davis et al. (1996), despite them being obtained from a single rehabilitated animal, but urge additional research into the diving patterns of the species.

To estimate time in view needed by the Laake estimator, we used results reported by Robertson et al. (2015), rescaled linearly for each survey program according to its target altitude and speed. We caution that Robertson's analysis was done for a de Havilland Twin Otter, which may have a different field of view than that of the other aircraft used here, which mainly comprised Cessna 337 Skymasters with flat windows. However, we note that McLellan et al. (2018) conducted a sensitivity analysis on the influence of the length of the "window of opportunity" to view beaked whales from a Cessna Skymaster on their final density estimates and found that they varied by only a few thousandths of an animal per kilometer when the window of opportunity more than doubled. Still, we urge additional program-specific research into estimation of availability bias.

To address the influence of group size on availability bias, we applied the group availability estimator of McLellan et al. (2018) on a per-observation basis. Following Palka et al. (2021), who also used that method, we assumed that individuals in the group dived asynchronously. The resulting g_{0A} corrections ranged from about 0.84 to 1.0 (Figure 59), with the majority of observations having a correction of 0.98 or higher, owing to large group sizes. We caution that the assumption of asynchronous diving can lead to an underestimation of density and abundance if diving is actually synchronous; see McLellan et al. (2018) for an exploration of this effect. However, if future research finds that this species conducts synchronous dives and characterizes the degree of synchronicity, the model can be updated to account for this knowledge.

Table 24: Perception bias corrections for Atlantic spotted dolphin applied to aerial surveys.

Surveys	Group Size	g_{0P}	g_{0P} Source
All	≤ 25	0.650	Palka et al. (2021): SEFSC
All	> 25	0.994	Carretta et al. (2000)

Table 25: Surface and dive intervals for Atlantic spotted dolphin used to estimate availability bias corrections.

Surface Interval (s)	Dive Interval (s)	Source
1.2	14.4	Davis et al. (1996)

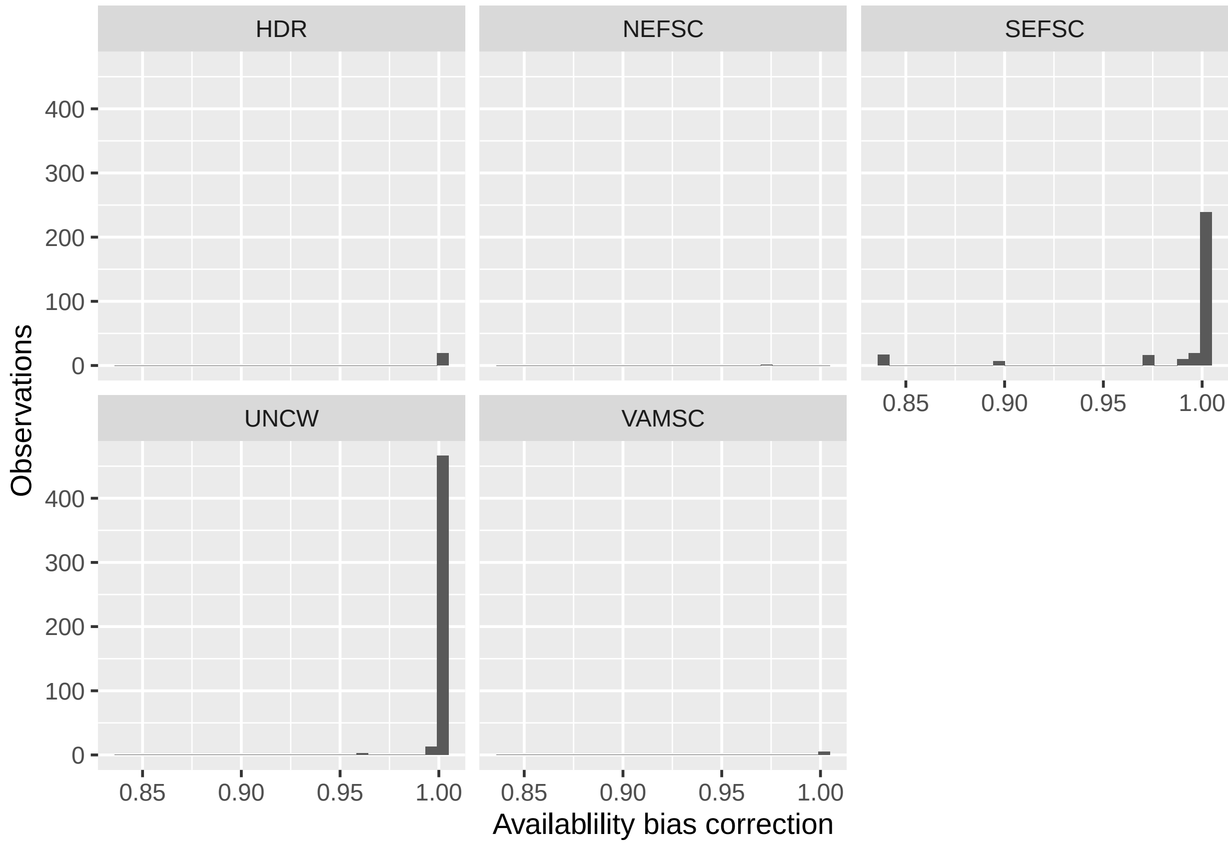


Figure 59: Availability bias corrections for Atlantic spotted dolphin for aerial surveys, by institution.

4.2 Shipboard Surveys

Most of the shipboard surveys in our analysis used high-power (25x150), pedestal-mounted binoculars. Similar to aerial surveys, Palka et al. (2021) developed perception bias corrections using two team, MRDS methodology (Burt et al. 2014) for high-power binocular surveys conducted in 2010-2017 by NOAA NEFSC and SEFSC during the AMAPPS program. These were the only extant perception bias estimates developed from high-power binocular surveys used in our analysis, aside from estimates developed earlier by Palka and colleagues (Palka 2006; Palka et al. 2017). Those earlier efforts utilized older methods and less data than their 2021 analysis, so we applied the Palka et al. (2021) estimates to all shipboard surveys that searched with high-power binoculars (Table 26).

A few surveys used naked eyes rather than high-power binoculars, but none of these programs prepared perception bias estimates for Atlantic spotted dolphin, nor could we locate any in the literature for shipboard naked eye observations of this species. As a proxy, we used the estimate from Palka (2006) developed for Atlantic white-sided dolphin for the AJ 99-02 naked eye survey.

For all surveys, to account for the influence of large group sizes on perception bias, we followed Barlow and Forney (2007) and set the perception bias correction factor for sightings of more than 20 animals to $g_{0P} = 0.97$. Given that the dive interval of this species (Table 25) was short relative to the amount of time a given patch of water remained in view to shipboard observers, we assumed that no availability bias correction was needed ($g_{0A} = 1$), following Palka et al. (2021).

Table 26: Perception and availability bias corrections for Atlantic spotted dolphin applied to shipboard surveys.

Surveys	Searching Method	Group Size	g_{0P}	g_{0P} Source	g_{0A}	g_{0A} Source
NEFSC	Binoculars	≤ 20	0.87	Palka et al. (2021): NEFSC	1	Assumed
SEFSC	Binoculars	≤ 20	0.62	Palka et al. (2021): SEFSC	1	Assumed
MCR	Naked eye	≤ 20	0.27	Palka et al. (2006)	1	Assumed
All	All	> 20	0.97	Barlow and Forney (2007)	1	Assumed

5 Density Model

The Atlantic spotted dolphin occurs in tropical and temperate waters of the Atlantic Ocean. In the North Atlantic, two ecotypes occur, which may be sub-species: a large, heavily-spotted form that inhabits the continental shelf and a smaller, less-spotted form that occurs offshore and around islands (Hayes et al. 2020). A recent genetic analysis of samples collected in the Gulf of Mexico, the western North Atlantic, and the Azores confirmed genetic differentiation between the ecotypes (Viricel and Rosel 2014), and an analysis of Atlantic spotted dolphin whistles reported statistically significant differences in several whistle characteristics between the ecotypes (Baron et al. 2008).

In the western North Atlantic, it can be difficult for observers to distinguish the offshore form of the Atlantic spotted dolphin from the pantropical spotted dolphin, and prior to 1999, NOAA reported a combined abundance estimate for the two species for this area (Waring et al. 2014). It has since been shown that full identifications could confidently be made south of Cape Hatteras (Waring et al. 2014). All of the spotted dolphin sightings that we had south of Cape Hatteras, going back to the earliest survey from 1992, were fully-resolved to the species level. In contrast, the more northerly offshore surveys we had prior to 1998 all reported the ambiguous identification "spotted dolphin". Beginning in 1998, all sightings of spotted dolphins were fully-resolved to the species level. To eliminate the chance that the species identification problem could bias the model, we restricted our analysis to surveys from 1998 and later.

The surveys available for modeling, spanning 1998-2020 (see Section 1), reported over 1300 sightings. The surveys generally did not specify which ecotype of Atlantic spotted dolphin was sighted. However, in an analysis of genetic samples obtained from 397 Atlantic spotted dolphins encountered in U.S. waters of the western North Atlantic, U.S. waters of the Gulf of Mexico, and near the Azores, Viricel and Rosel (2014) reported statistically-significant differences in depth, sea surface temperature, and turbidity between the ecotypes as defined through genetic clustering. In our study area, Hayes et al. (2020) described the shelf ecotype as usually occurring inside or near the 200 m isobath, and the offshore ecotype occurring in continental slope waters. Given the distinct depth preferences of the two ecotypes, we split the study area into two models at the 300 m isobath, hereafter referred to as the "Shelf" or "Shallower than 300m" model and the "Offshore" or "Deeper than 300m" model. We chose this depth rather than the 200 m given by Hayes et al. after visual and statistical exploration of the available sightings. This was a pragmatical modeling decision, and we do not imply at this time that it is the optimal value for differentiating the ecotypes, or that it otherwise has specific ecological importance for the species.

5.1 Shelf Model

Nearly 1100 sightings were available for this model, mainly distributed between Cape Canaveral and Chesapeake Bay (Figure 60). Viricel and Rosel (2014) reported that there was no evidence for migratory patterns in Atlantic spotted dolphins in the western North Atlantic, and we could find no description in the literature that indicated a clear seasonal switch in the species' relationship to environmental covariates (as with certain baleen whales migrating between cold feeding grounds and warm calving grounds), so we fitted a year-round model that incorporated all available survey data, rather than breaking the year into separate seasonal models. However, during exploratory analysis we observed an apparent seasonal shift in sightings in monthly aggregate maps of survey data (see figures in Section 6.1), with large numbers of sightings reported north of Cape Hatteras in June-September, and therefore anticipated that model predictions would depict seasonal movements driven by dynamic environmental covariates.

The model selection procedure was straightforward. When ranked by REML score (Wood 2011), the highest ranked models with climatological covariates outranked those with contemporaneous covariates and explained 1.7% more deviance. We selected the highest ranked climatological model, which included seven terms (Table 27). Functional relationships (Figure 63) showed a steady rise in density as either sea surface temperature or salinity increased, corresponding to the warm, salty waters of the southern continental shelf. The relationship with distance to shore was hump-shaped, indicating higher densities in mid-shelf waters. Also consistent with this was a negative relationship with bottom temperature, indicating lower densities at higher bottom temperatures, which tend to occur in shallow waters close to shore. Further supporting a mid-shelf concentration was the relationship with distance to the 125 m isobath, which turned sharply negative approaching the isobath and extending beyond it over the continental slope. Finally, the model fitted a positive relationship to the VGPM covariate, indicating higher density in more productive waters, and a positive relationship with distance to strong SST fronts, which likely indicated an avoidance of the Gulf Stream, which traverses the eastern edge of the modeled region.

Extrapolation diagnostics indicated a small univariate extrapolation of the VGPM covariate in January and February at the top of the Scotian Shelf (Figure 74), where no density was predicted; this was no cause for concern. The diagnostics also indicated some additional univariate and multivariate extrapolation in March and April along inshore central Florida (Figure 75), possibly driven by sea surface salinity. High but not excessive density was predicted in the vicinity of this extrapolation (Figures 94-95). While we consider the predictions plausible, we recommend additional surveying of coastal Florida in spring months with protocols suitable for small cetaceans (e.g. AMAPPS), to improve the statistical confidence of future models that include this area.

5.1.1 Final Model

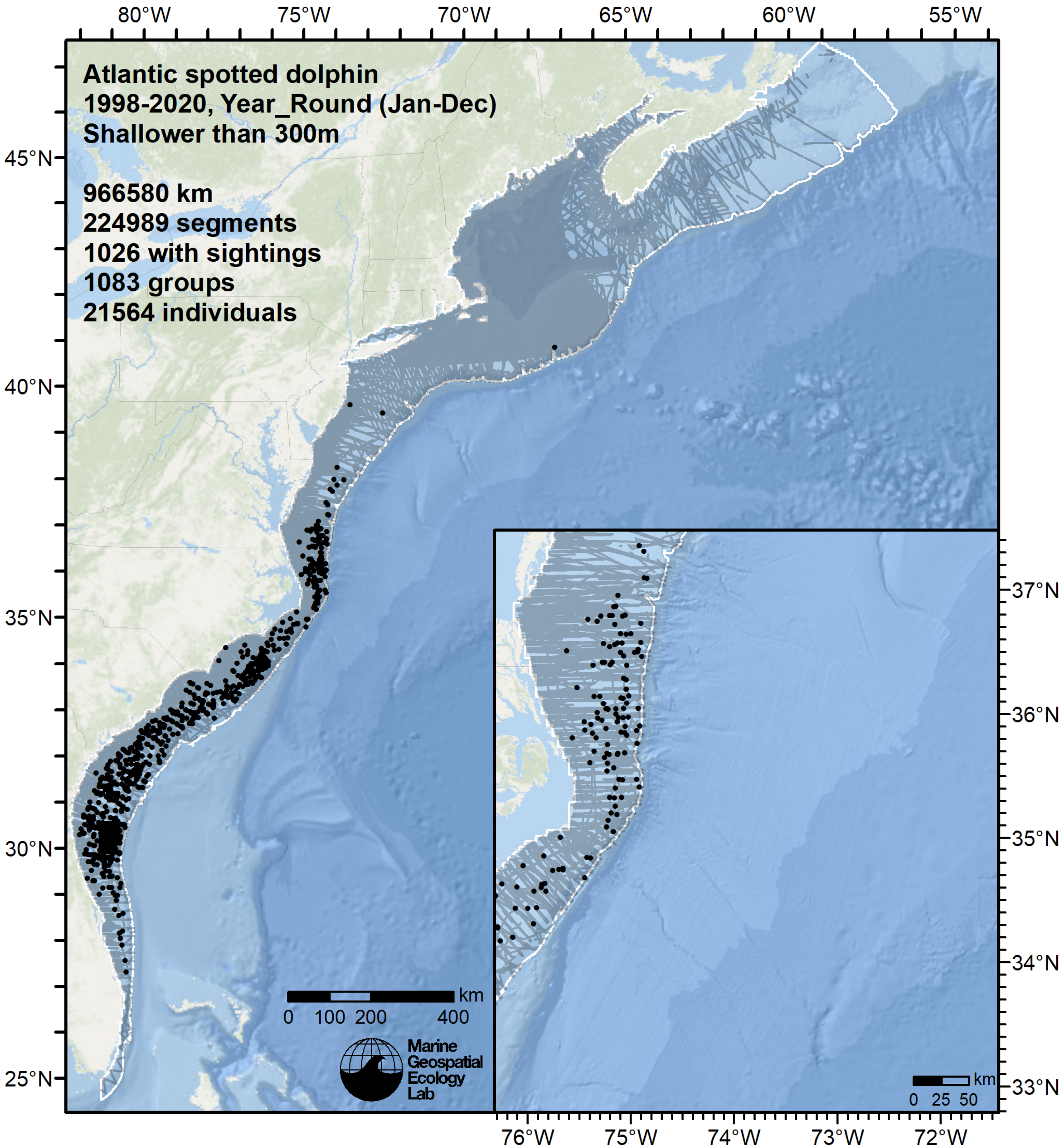


Figure 60: Survey segments used to fit the model for the region Shallower than 300m. Black points indicate segments with observations.

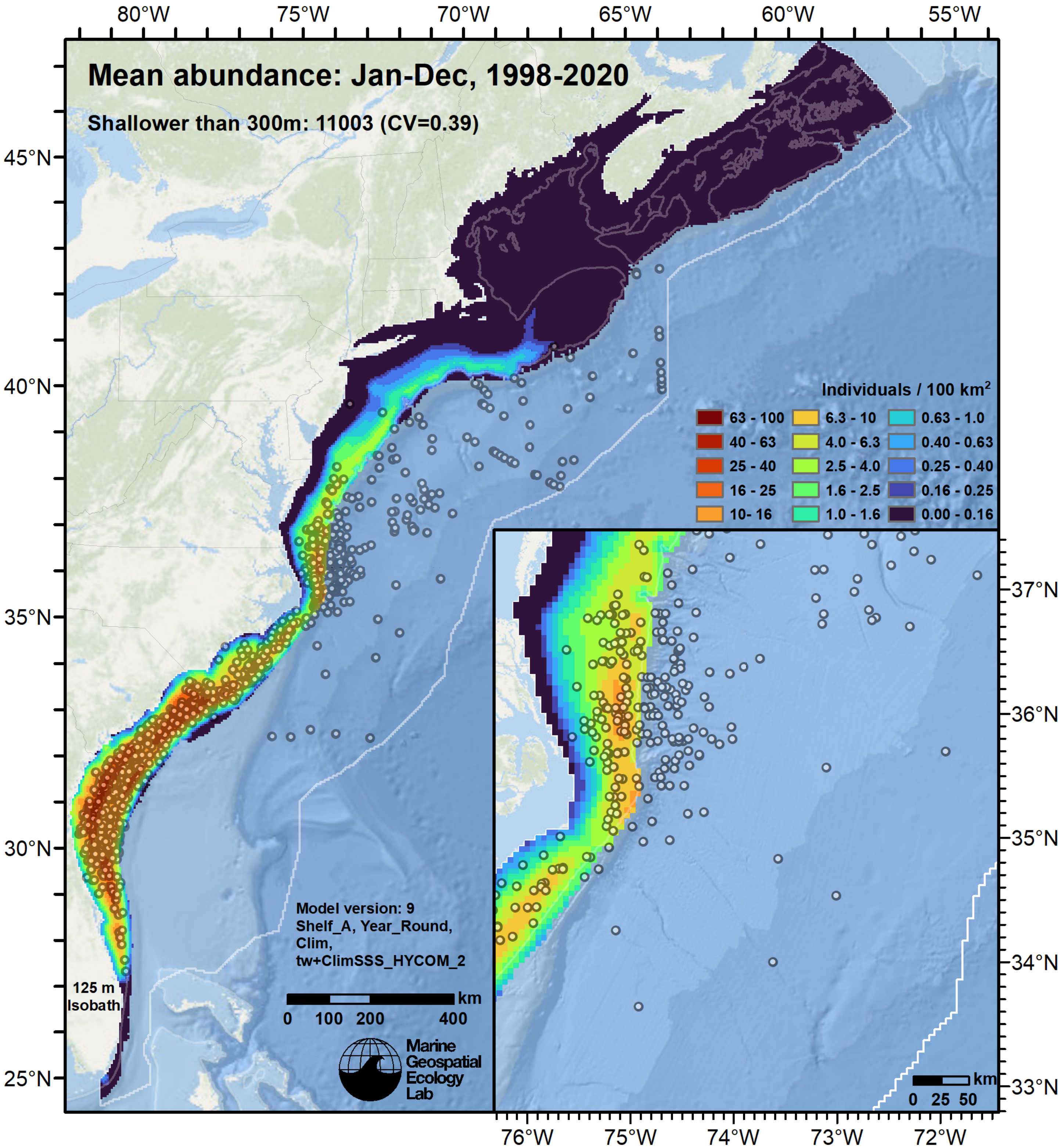


Figure 61: Atlantic spotted dolphin mean density for the indicated period, as predicted by the model for the region Shallower than 300m. Open circles indicate segments with observations. Mean total abundance and its coefficient of variation (CV) are given in the subtitle. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for seasonal variability in dynamic covariates but not interannual variability in them, as these covariates were monthly climatological averages.

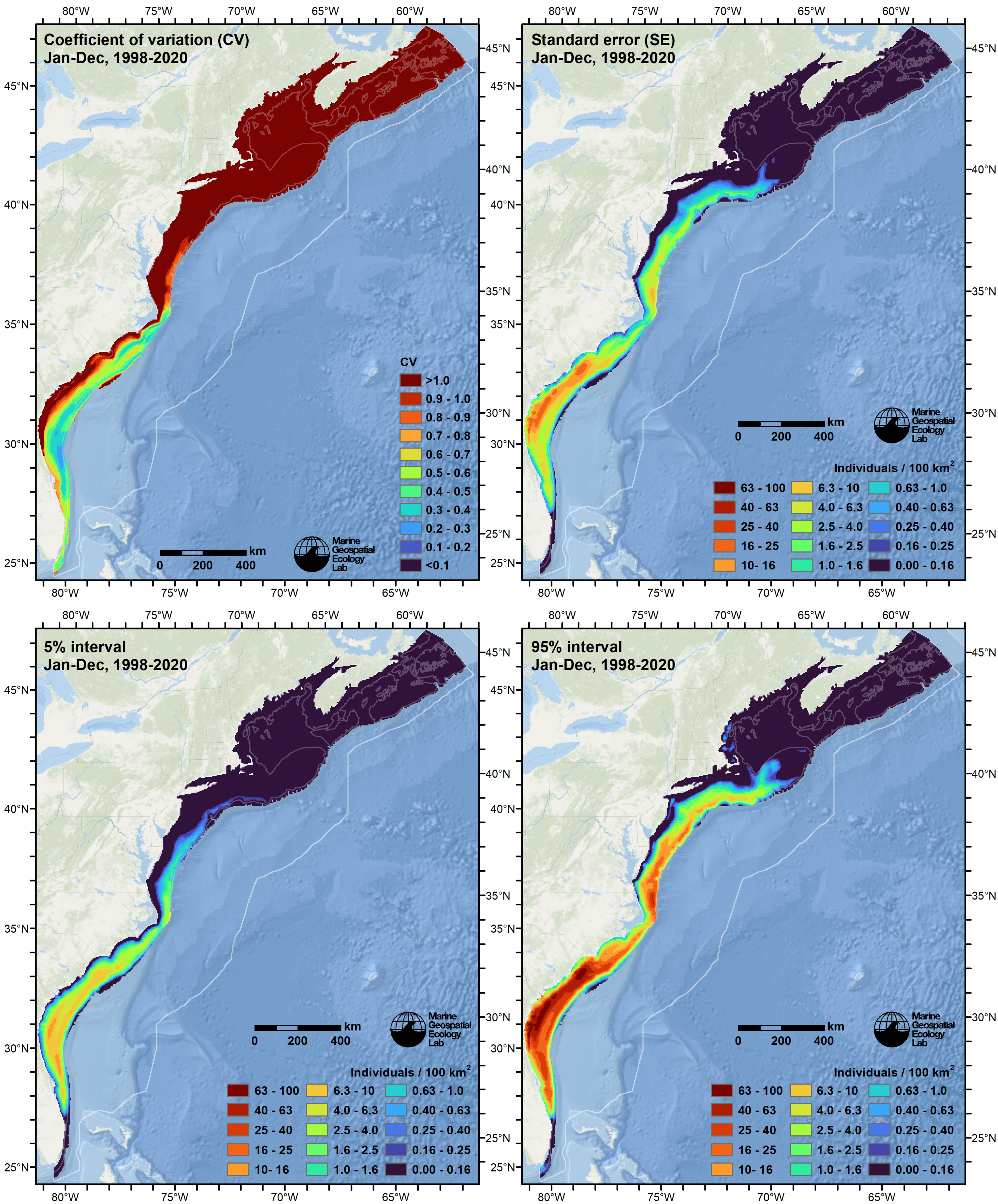
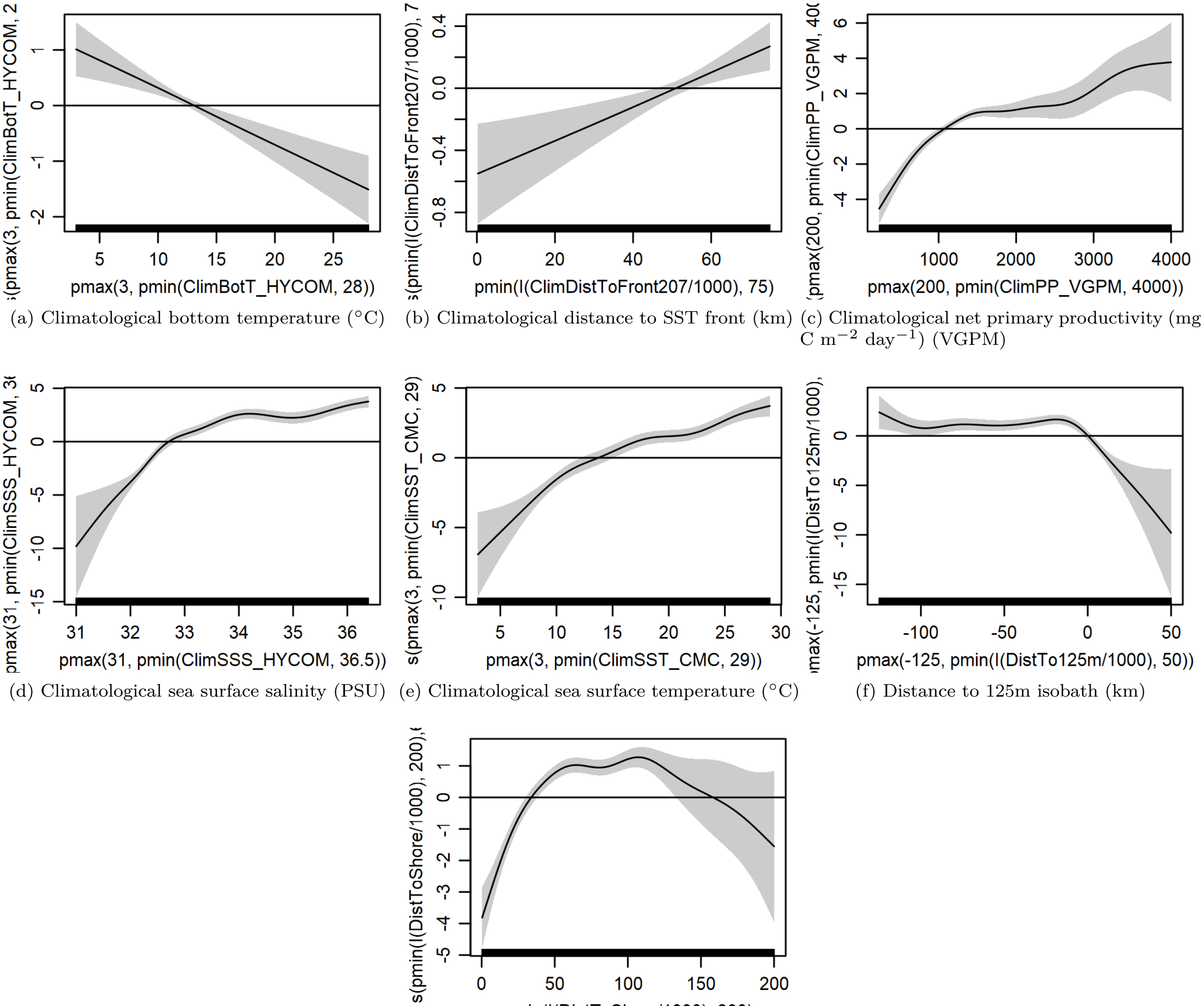


Figure 62: Uncertainty statistics for the Atlantic spotted dolphin mean density surface (Figure 61) predicted by the model for the region Shallower than 300m. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for seasonal variability in dynamic covariates but not interannual variability in them, as these covariates were monthly climatological averages.

Statistical output for this model:

```
Family: Tweedie(p=1.355)
Link function: log

Formula:
IndividualsCorrected ~ offset(log(SegmentArea)) + s(pmin(I(DistToShore/1000),
    200), bs = "ts") + s(pmax(-125, pmin(I(DistTo125m/1000),
    50)), bs = "ts") + s(pmax(3, pmin(ClimSST_CMC, 29)), bs = "ts") +
    s(pmax(3, pmin(ClimBotT_HYCOM, 28)), bs = "ts") + s(pmax(31,
    pmin(ClimSSS_HYCOM, 36.5)), bs = "ts") + s(pmin(I(ClimDistToFront207/1000),
    75), bs = "ts") + s(pmax(200, pmin(ClimPP_VGPM, 4000)), bs = "ts")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -22.1491     0.3144  -70.44   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                                          edf Ref.df      F  p-value
s(pmin(I(DistToShore/1000), 200))       6.277      9 13.556  < 2e-16 ***
s(pmax(-125, pmin(I(DistTo125m/1000), 50))) 6.612      9 11.536  < 2e-16 ***
s(pmax(3, pmin(ClimSST_CMC, 29)))       5.334      9 20.052  < 2e-16 ***
s(pmax(3, pmin(ClimBotT_HYCOM, 28)))    1.188      9  2.762 1.03e-06 ***
s(pmax(31, pmin(ClimSSS_HYCOM, 36.5)))  6.231      9 27.005  < 2e-16 ***
s(pmin(I(ClimDistToFront207/1000), 75)) 1.015      9  1.359 0.000201 ***
s(pmax(200, pmin(ClimPP_VGPM, 4000)))   6.014      9 18.169  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.019   Deviance explained = 40.1%
-REML = 9636.2  Scale est. = 52.941    n = 224989

Method: REML   Optimizer: outer newton
full convergence after 13 iterations.
Gradient range [-0.003304147,0.001627003]
(score 9636.193 & scale 52.94109).
Hessian positive definite, eigenvalue range [0.4709211,4165.829].
Model rank =  64 / 64

Basis dimension (k) checking results. Low p-value (k-index<1) may
indicate that k is too low, especially if edf is close to k'.

                                          k'  edf k-index p-value
s(pmin(I(DistToShore/1000), 200))       9.00 6.28    0.73   0.005 **
s(pmax(-125, pmin(I(DistTo125m/1000), 50))) 9.00 6.61    0.72  <2e-16 ***
s(pmax(3, pmin(ClimSST_CMC, 29)))       9.00 5.33    0.64  <2e-16 ***
s(pmax(3, pmin(ClimBotT_HYCOM, 28)))    9.00 1.19    0.64  <2e-16 ***
s(pmax(31, pmin(ClimSSS_HYCOM, 36.5)))  9.00 6.23    0.59  <2e-16 ***
s(pmin(I(ClimDistToFront207/1000), 75)) 9.00 1.01    0.77   0.025 *
s(pmax(200, pmin(ClimPP_VGPM, 4000)))   9.00 6.01    0.74   0.005 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



(a) Climatological bottom temperature (°C)

(b) Climatological distance to SST front (km)

(c) Climatological net primary productivity (mg C m^{-2} day^{-1}) (VGPM)

(d) Climatological sea surface salinity (PSU)

(e) Climatological sea surface temperature (°C)

(f) Distance to 125m isobath (km)

(g) Distance to shore (km)

Figure 63: Functional plots for the final model for the region Shallower than 300m. Transforms and other treatments are indicated in axis labels. *log10* indicates the covariate was $\log_{10}$ transformed. *pmax* and *pmin* indicate the covariate's minimum and maximum values, respectively, were Winsorized to the values shown. Winsorization was used to prevent runaway extrapolations during prediction when covariates exceeded sampled ranges, or for ecological reasons, depending on the covariate. */1000* indicates meters were transformed to kilometers for interpretation convenience.

Table 27: Covariates used in the final model for the region Shallower than 300m.

Covariate	Description
ClimBotT_HYCOM	Climatological monthly mean bottom temperature (°C) from the HYCOM GOFS 3.1 1/12° ocean model (Chassignet et al. (2009))
ClimDistToFront207	Climatological monthly mean distance (km) to the closest sea surface temperature front detected in daily GHRSST Level 4 CMC0.2deg and CMC0.1deg images (Brasnett (2008); Canada Meteorological Center (2012); Meissner et al. (2016); Canada Meteorological Center (2016)) with MGET's implementation of the Canny edge detector (Roberts et al. (2010); Canny (1986))
ClimPP_VGPM	Climatological monthly mean net primary productivity (mg C m^{-2} day^{-1}) from the Vertically Generalized Production Model (VGPM) (Behrenfeld and Falkowski (1997))

Table 27: Covariates used in the final model for the region Shallower than 300m. *(continued)*

Covariate	Description
ClimSSS_HYCOM	Climatological monthly mean sea surface salinity (PSU) from the HYCOM GOFS 3.1 1/12° ocean model (Chassignet et al. (2009))
ClimSST_CMC	Climatological monthly mean sea surface temperature (°C) from GHRSST Level 4 CMC0.2deg and CMC0.1deg (Brasnett (2008); Canada Meteorological Center (2012); Meissner et al. (2016); Canada Meteorological Center (2016))
DistTo125m	Distance (km) to the 125m isobath, derived from SRTM30_PLUS (Becker et al. (2009))
DistToShore	Distance (km) to shore excluding Bermuda and Sable Island, derived from SRTM30_PLUS (Becker et al. (2009))

5.1.2 Diagnostic Plots

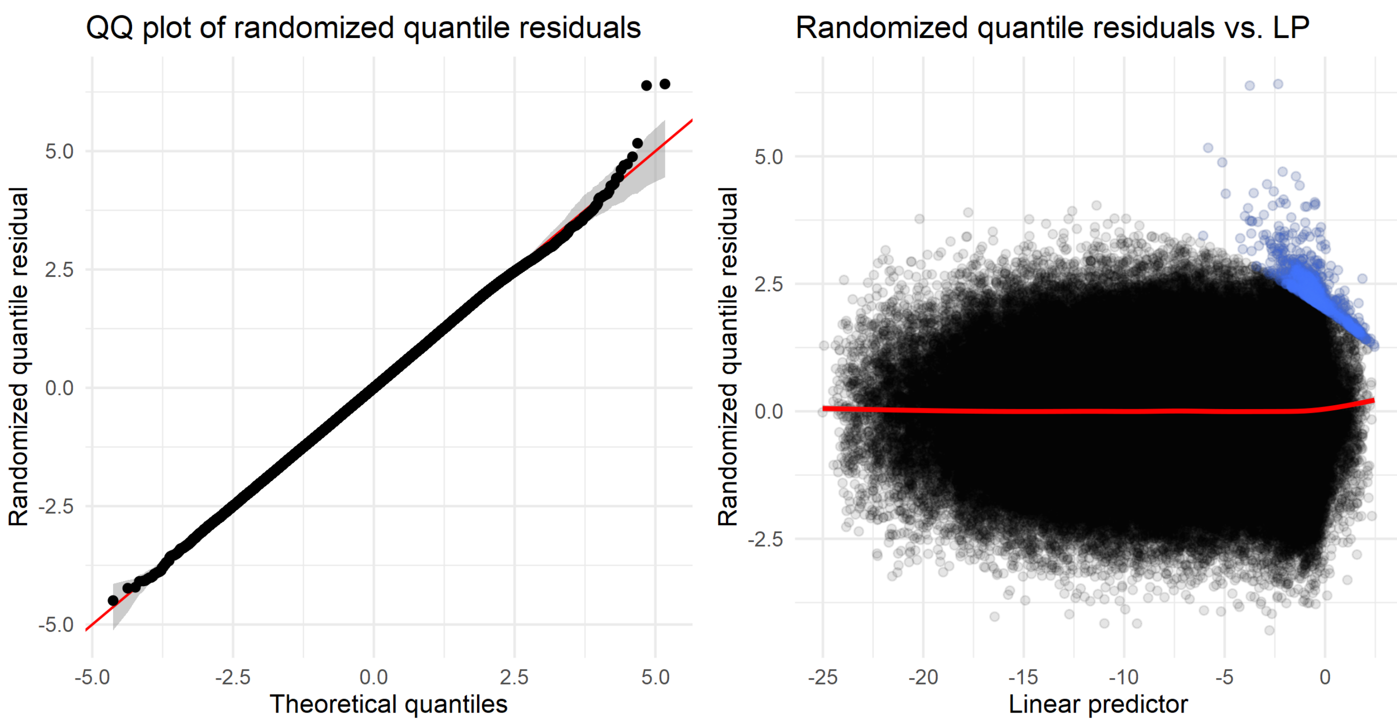


Figure 64: Residual plots for the final model for the region Shallower than 300m.

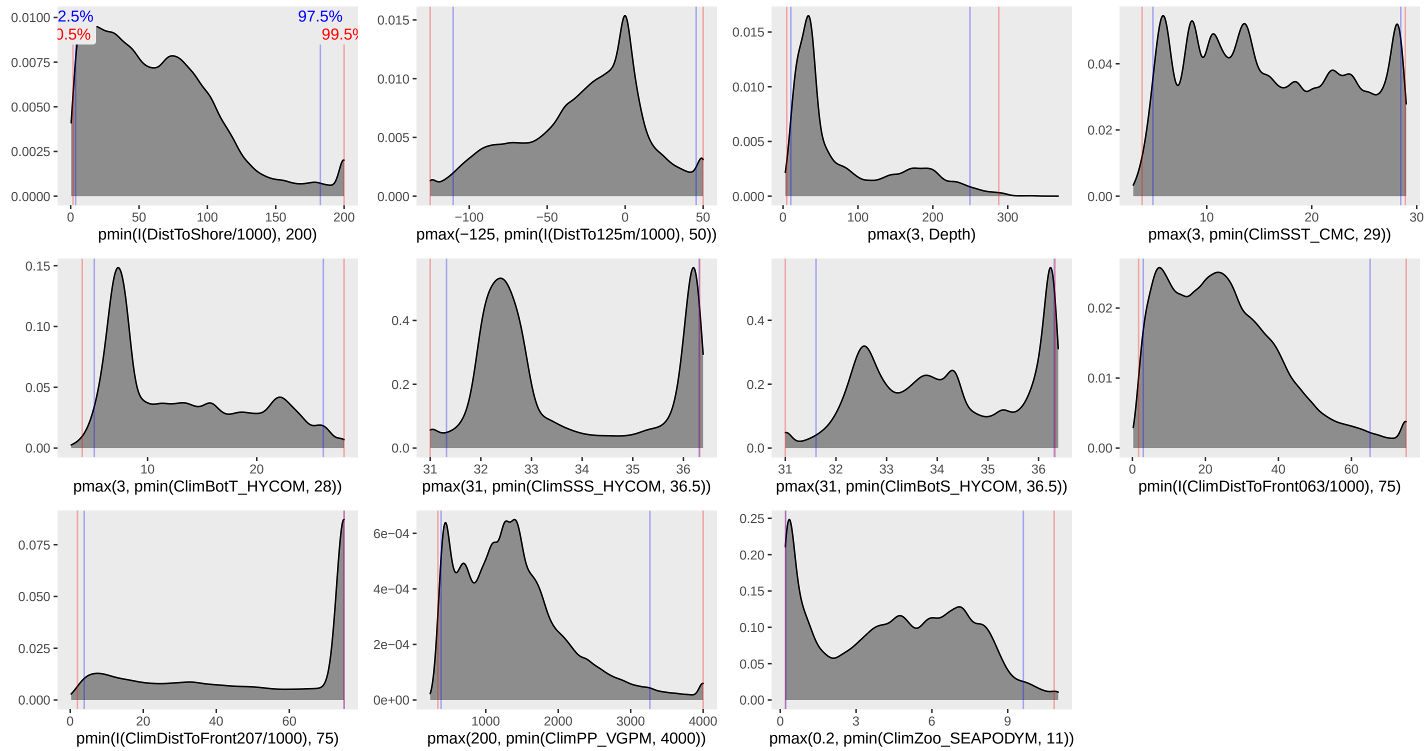


Figure 65: Density histograms showing the distributions of the covariates considered during the final model selection step. The final model may have included only a subset of the covariates shown here (see Figure 63), and additional covariates may have been considered in preceding selection steps. Red and blue lines enclose 99% and 95% of the distributions, respectively. Transforms and other treatments are indicated in axis labels. *log10* indicates the covariate was $\log_{10}$ transformed. *pmax* and *pmin* indicate the covariate's minimum and maximum values, respectively, were Winsorized to the values shown. Winsorization was used to prevent runaway extrapolations during prediction when covariates exceeded sampled ranges, or for ecological reasons, depending on the covariate. */1000* indicates meters were transformed to kilometers for interpretation convenience.

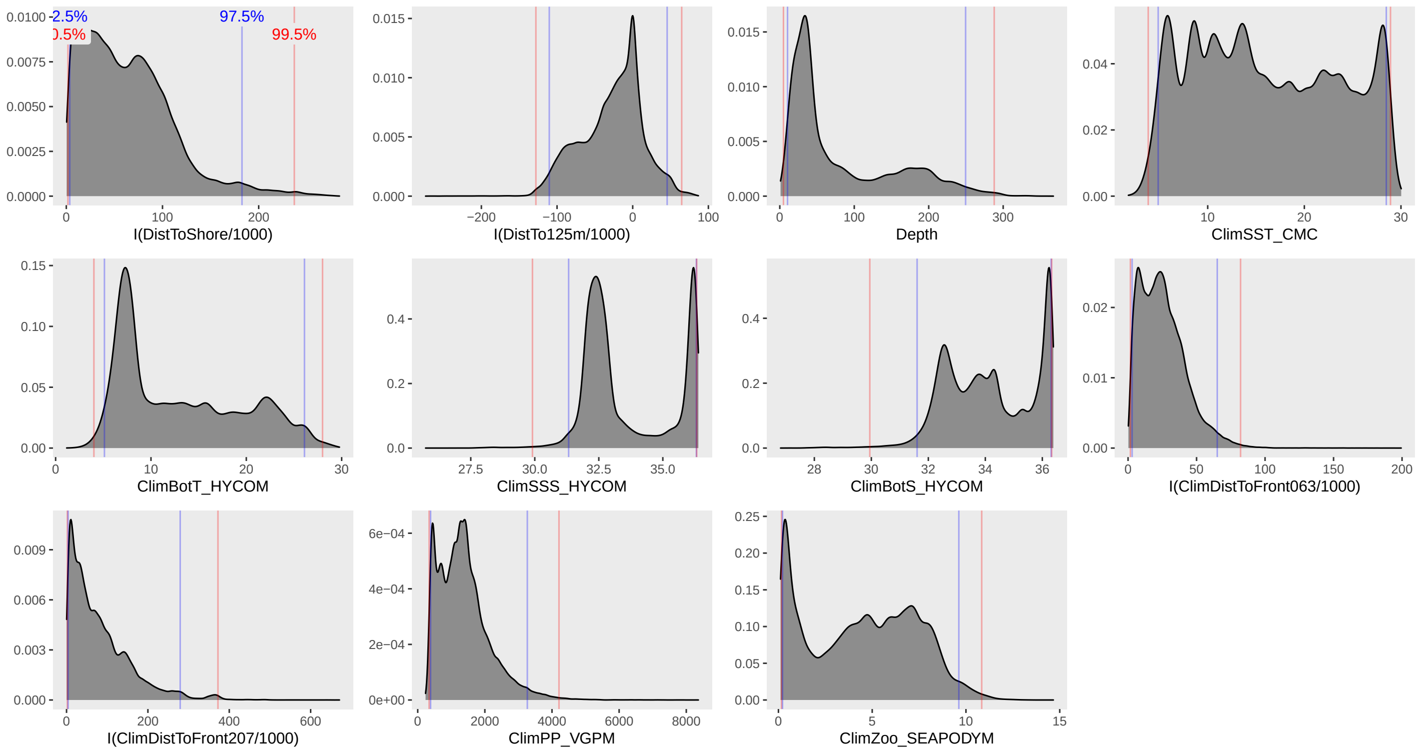


Figure 66: Density histograms shown in Figure 65 replotted without Winsorization, to show the full range of sampling represented by survey segments.

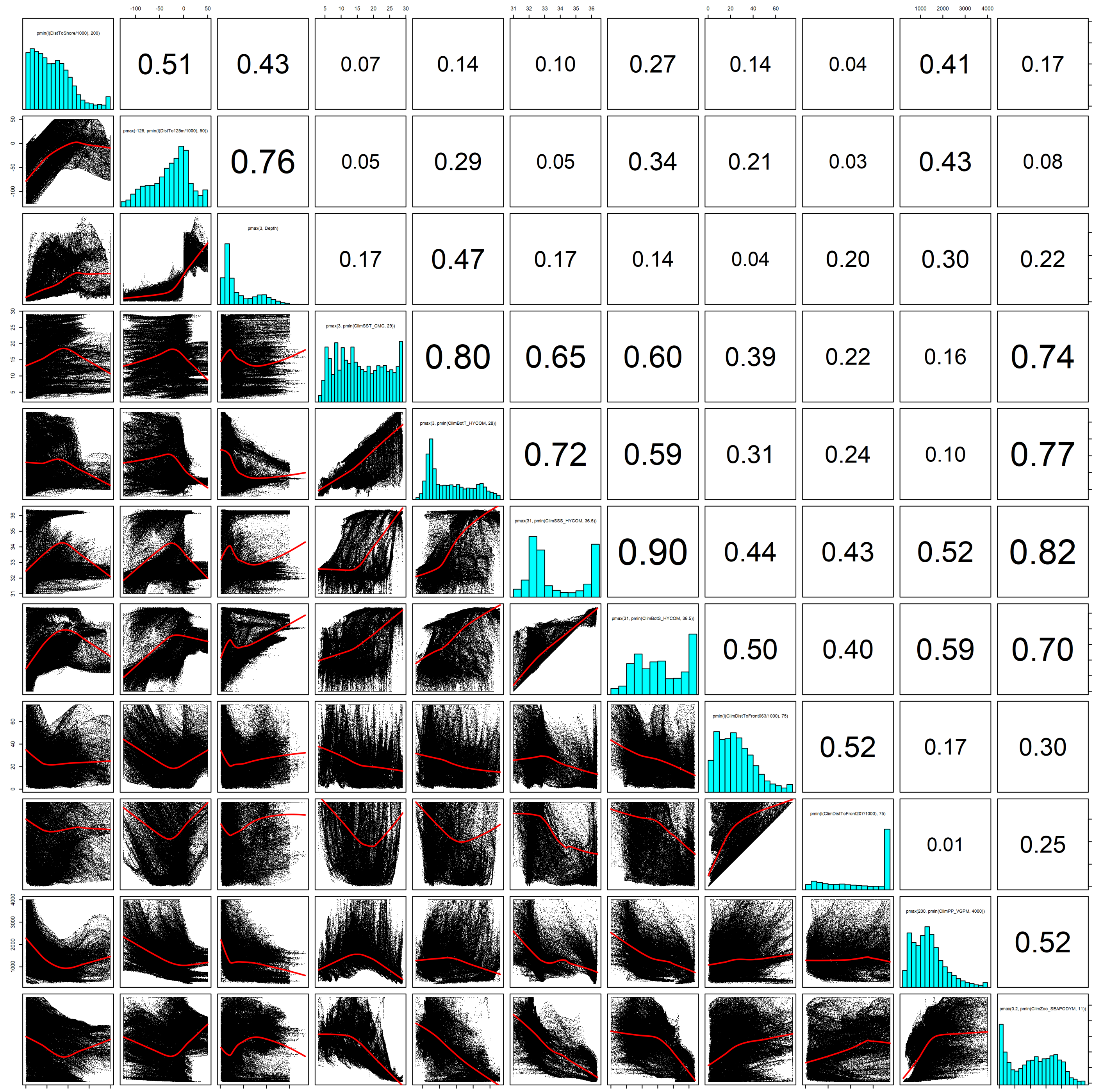


Figure 67: Scatterplot matrix of the covariates considered during the final model selection step. The final model may have included only a subset of the covariates shown here (see Figure 63), and additional covariates may have been considered in preceding selection steps. Covariates are transformed and Winsorized as shown in Figure 65. This plot is used to check simple correlations between covariates (via pairwise Pearson coefficients above the diagonal) and visually inspect for concurvity (via scatterplots and red lowess curves below the diagonal).

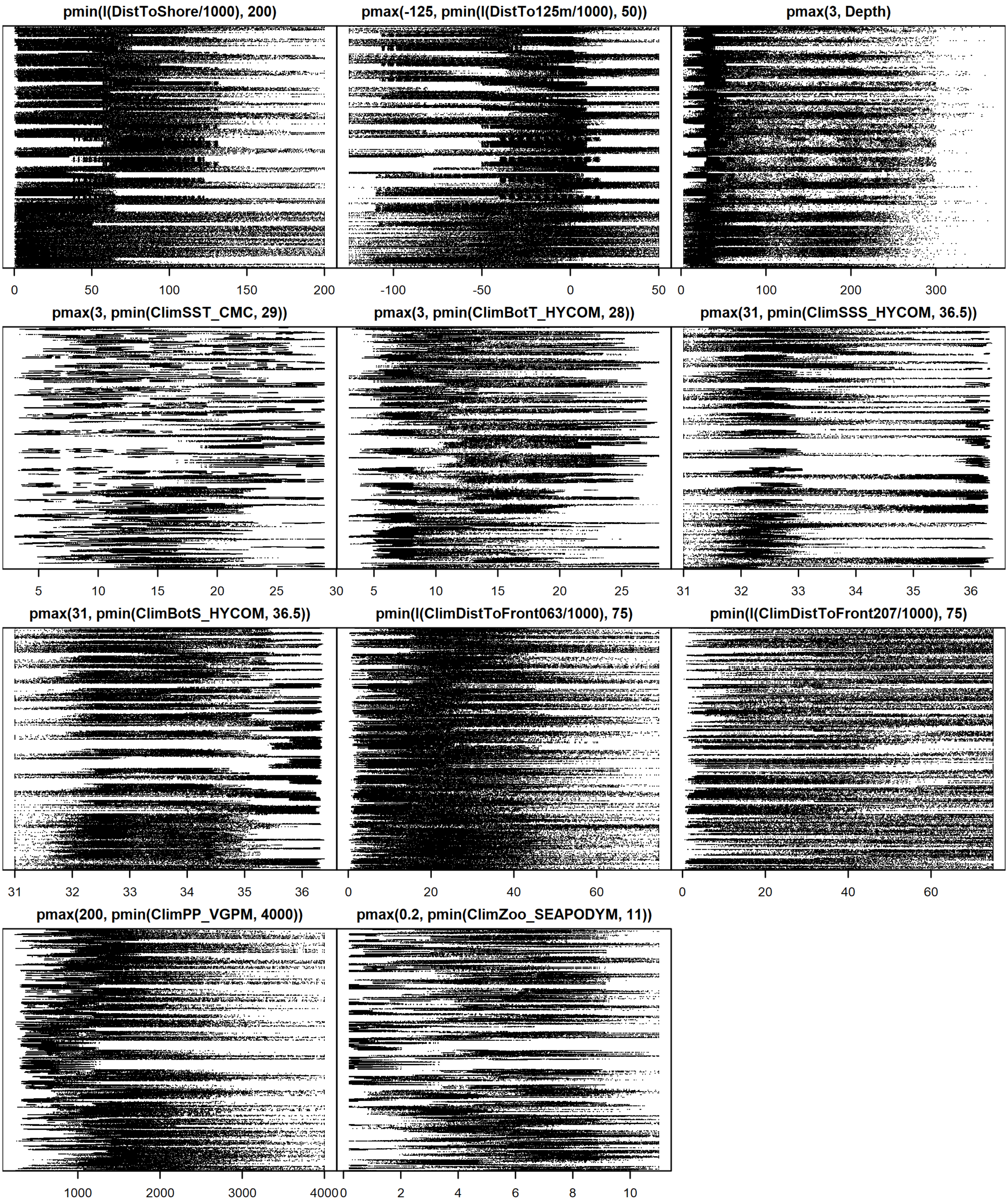
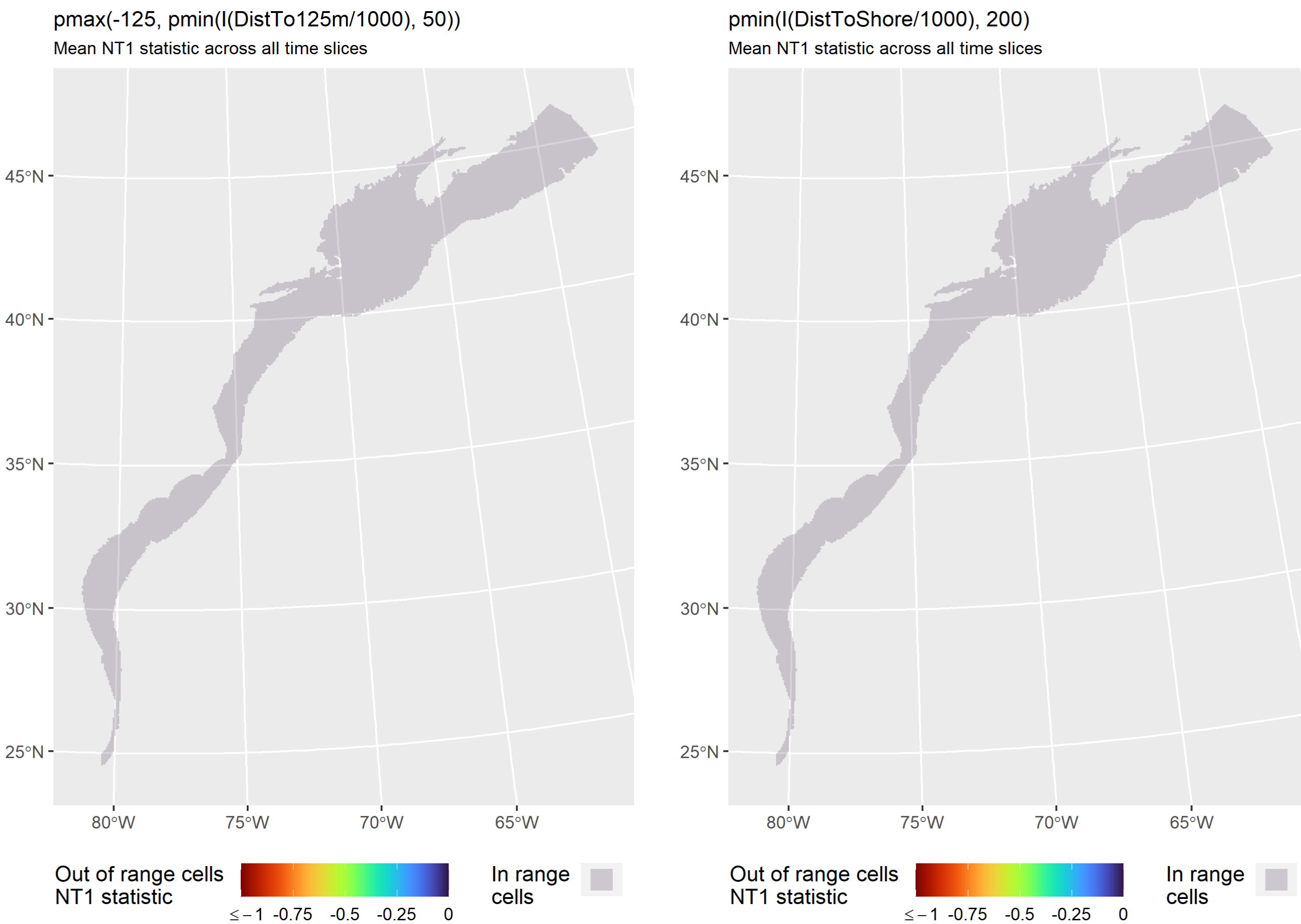


Figure 68: Dotplot of the covariates considered during the final model selection step. The final model may have included only a subset of the covariates shown here (see Figure 63), and additional covariates may have been considered in preceding selection steps. Covariates are transformed and Winsorized as shown in Figure 65. This plot is used to check for suspicious patterns and outliers in the data. Points are ordered vertically by segment ID, sequentially in time.

5.1.3 Extrapolation Diagnostics

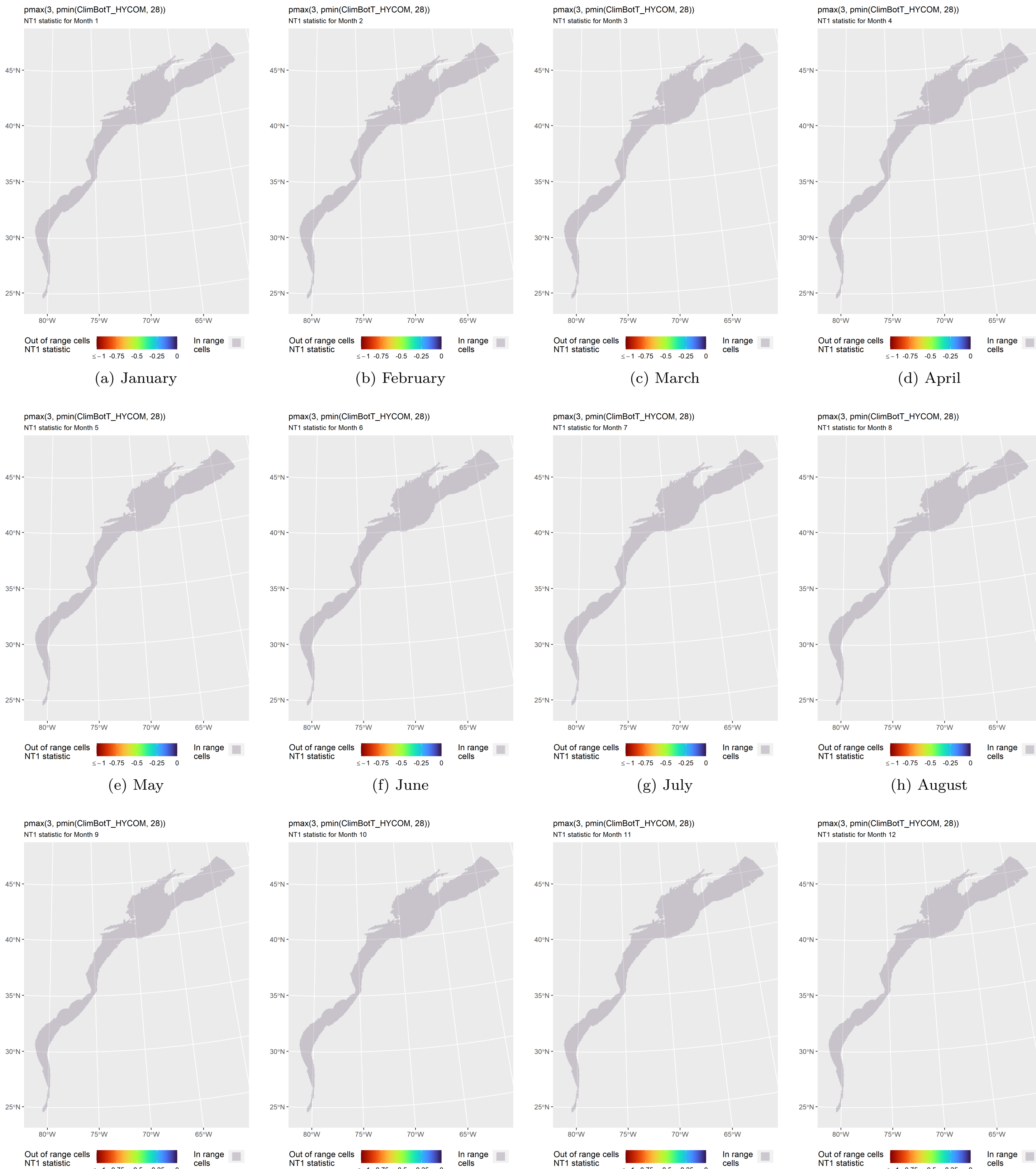
5.1.3.1 Univariate Extrapolation



(a) DistTo125m covariate

(b) DistToShore covariate

Figure 69: NT1 statistic (Mesgaran et al. (2014)) for static covariates used in the model for the region Shallower than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there. Areas within the sampled range appear in gray, indicating it did not occur.

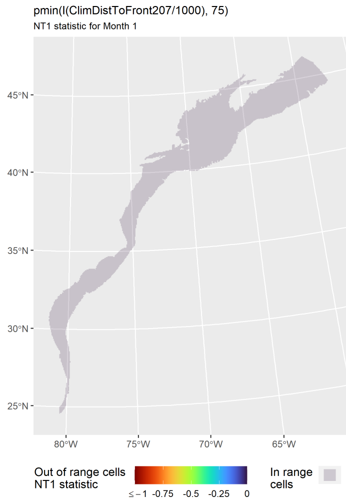


(a) January (b) February (c) March (d) April

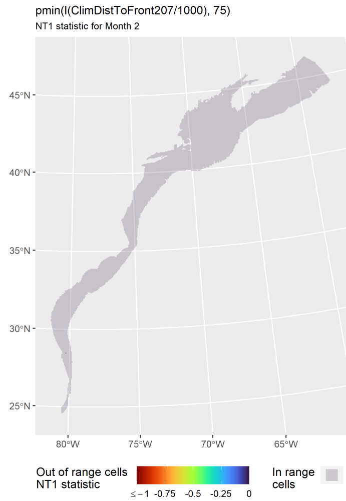
(e) May (f) June (g) July (h) August

(i) September (j) October (k) November (l) December

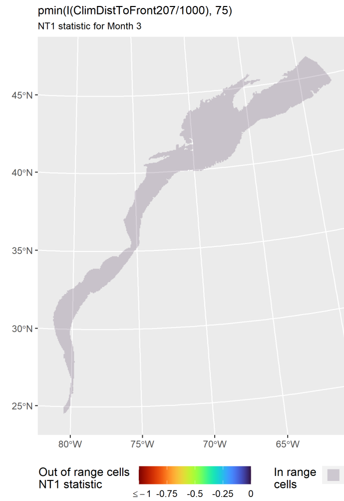
Figure 70: NT1 statistic (Mesgaran et al. (2014)) for the ClimBotT_HYCOM covariate in the model for the region Shallower than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there during the month. Areas within the sampled range appear in gray, indicating it did not occur.



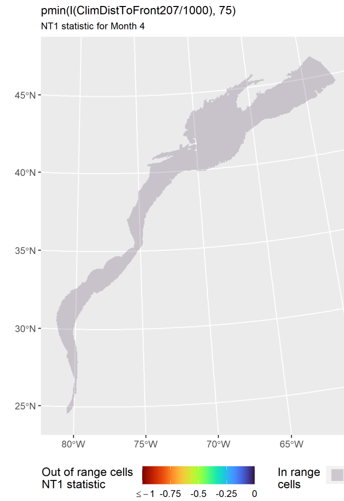
(a) January



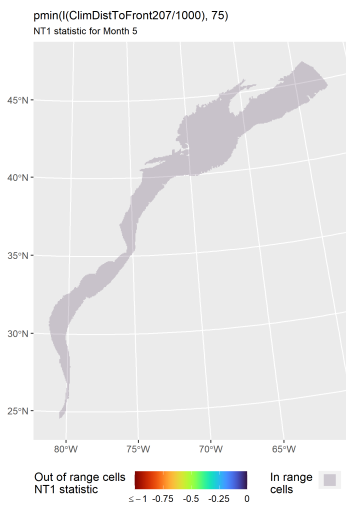
(b) February



(c) March



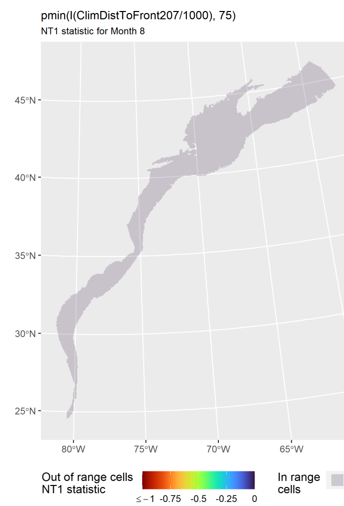
(d) April



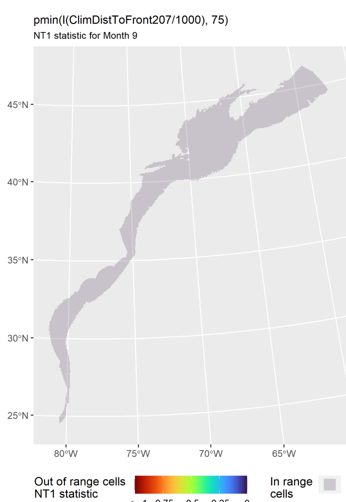
(e) May

(f) June

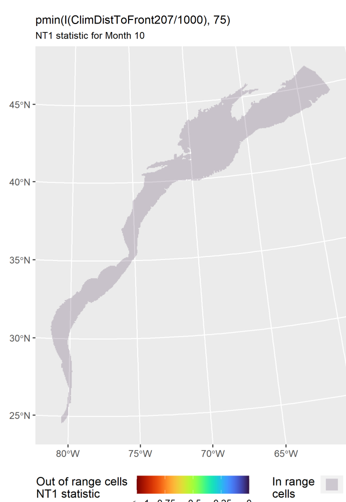
(g) July



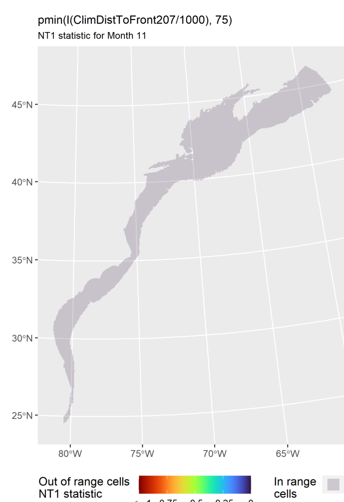
(h) August



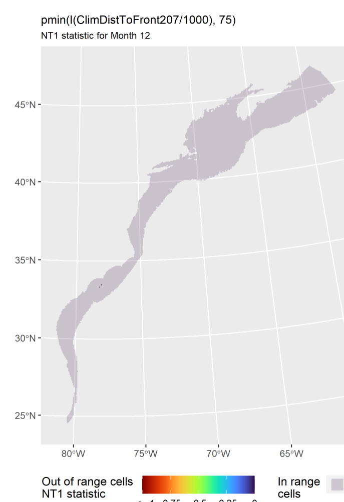
(i) September



(j) October

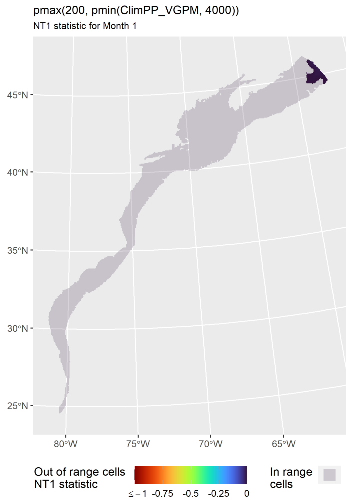


(k) November

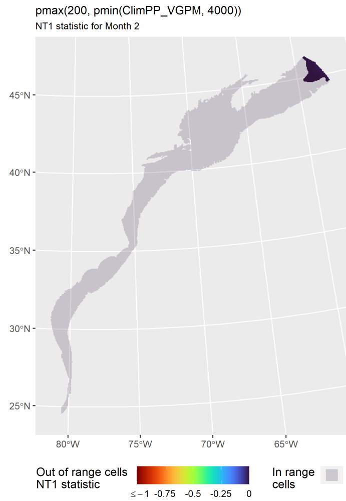


(l) December

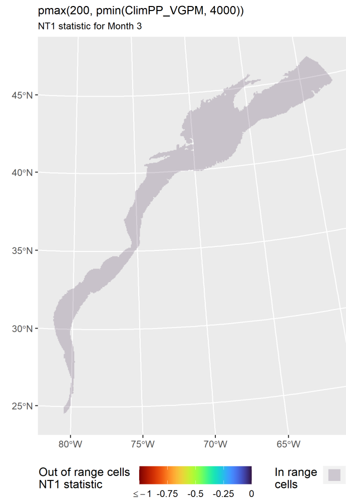
Figure 71: NT1 statistic (Mesgaran et al. (2014)) for the ClimDistToFront207 covariate in the model for the region Shallower than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there during the month. Areas within the sampled range appear in gray, indicating it did not occur.



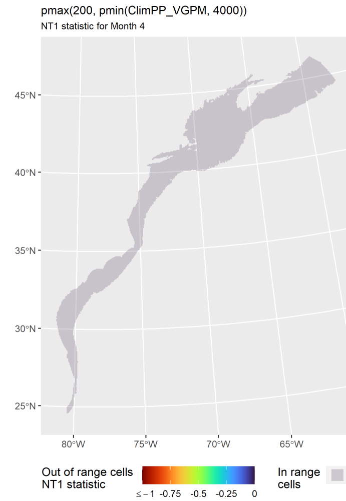
(a) January



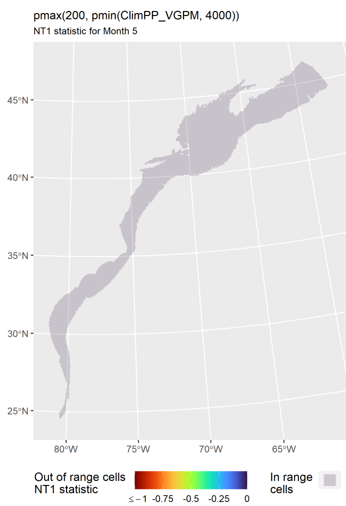
(b) February



(c) March

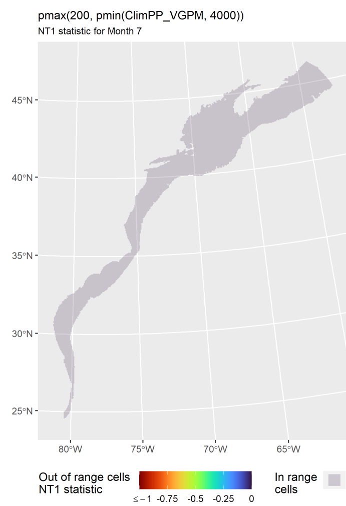


(d) April

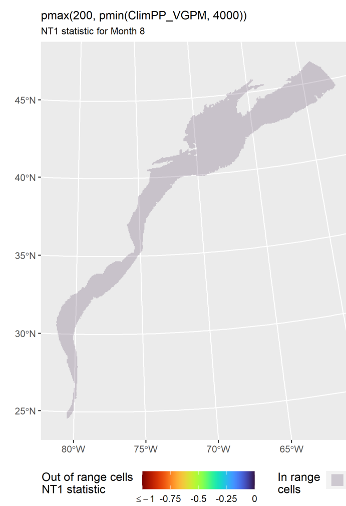


(e) May

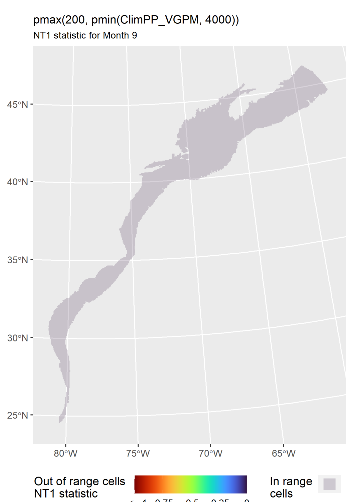
(f) June



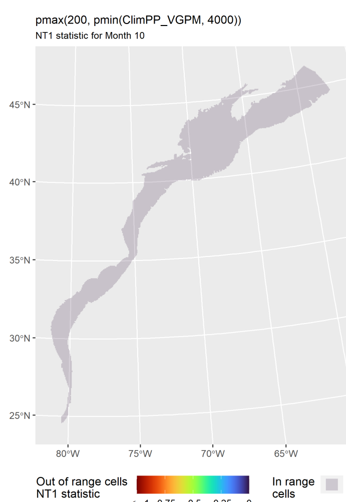
(g) July



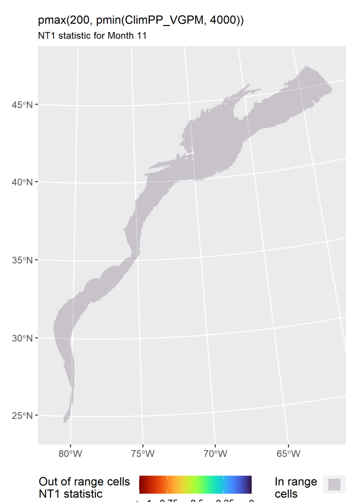
(h) August



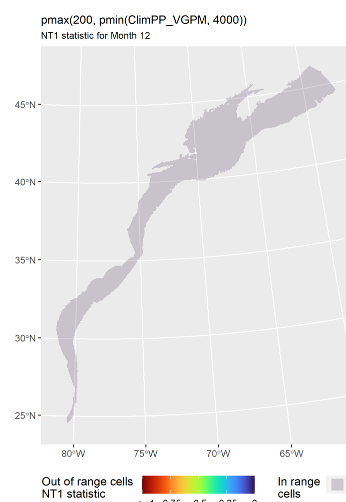
(i) September



(j) October

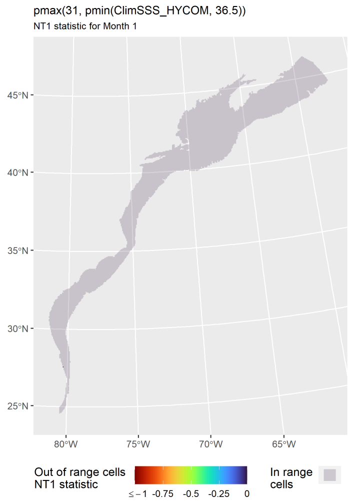


(k) November

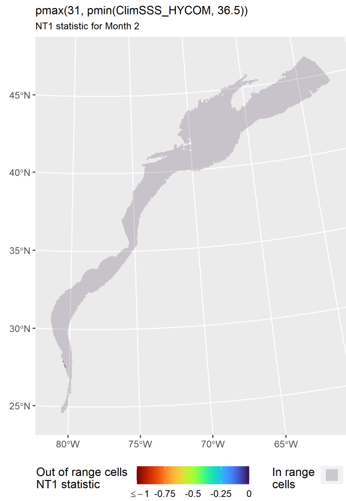


(l) December

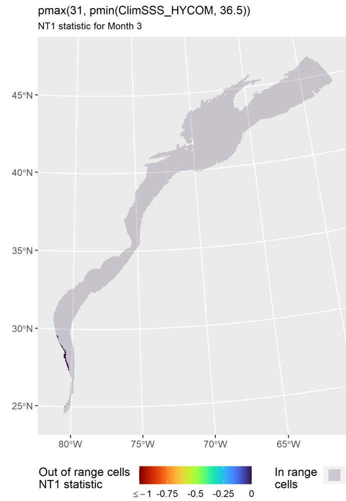
Figure 72: NT1 statistic (Mesgaran et al. (2014)) for the ClimPP_VGPM covariate in the model for the region Shallower than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there during the month. Areas within the sampled range appear in gray, indicating it did not occur.



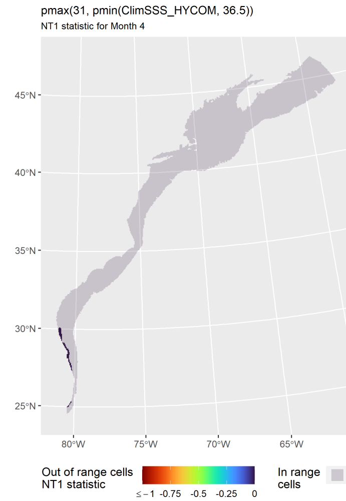
(a) January



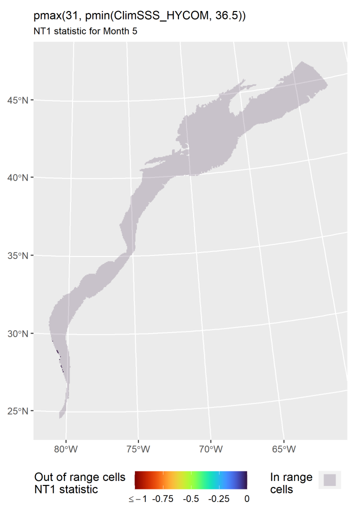
(b) February



(c) March

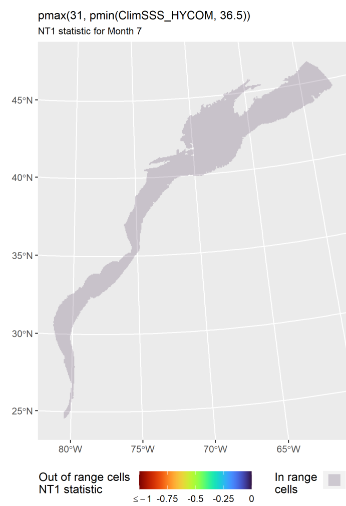


(d) April

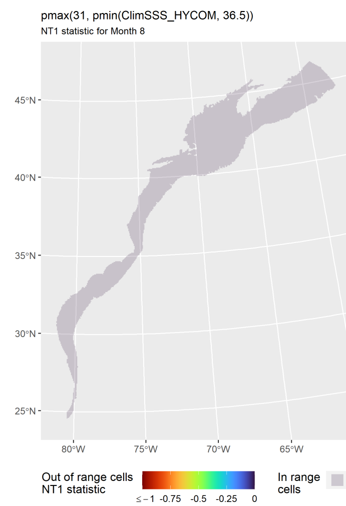


(e) May

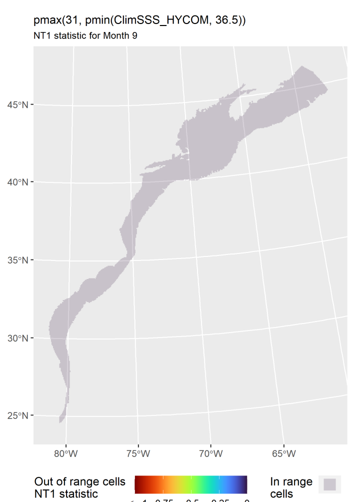
(f) June



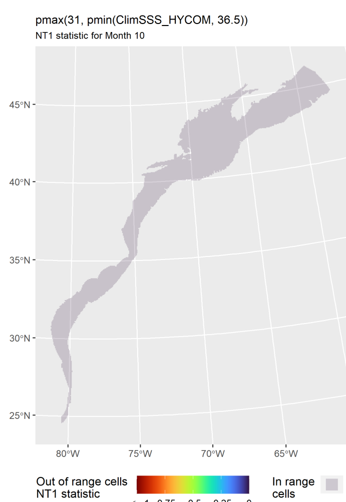
(g) July



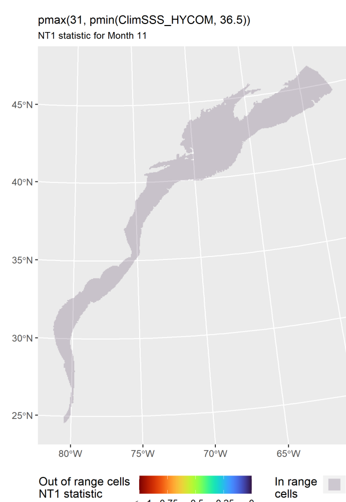
(h) August



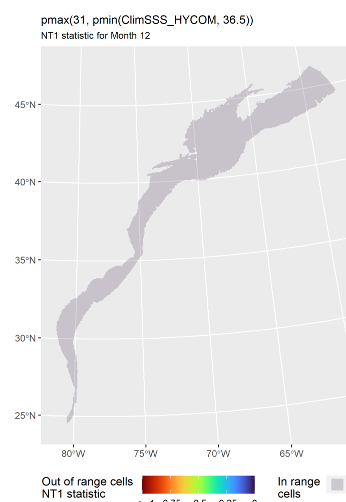
(i) September



(j) October

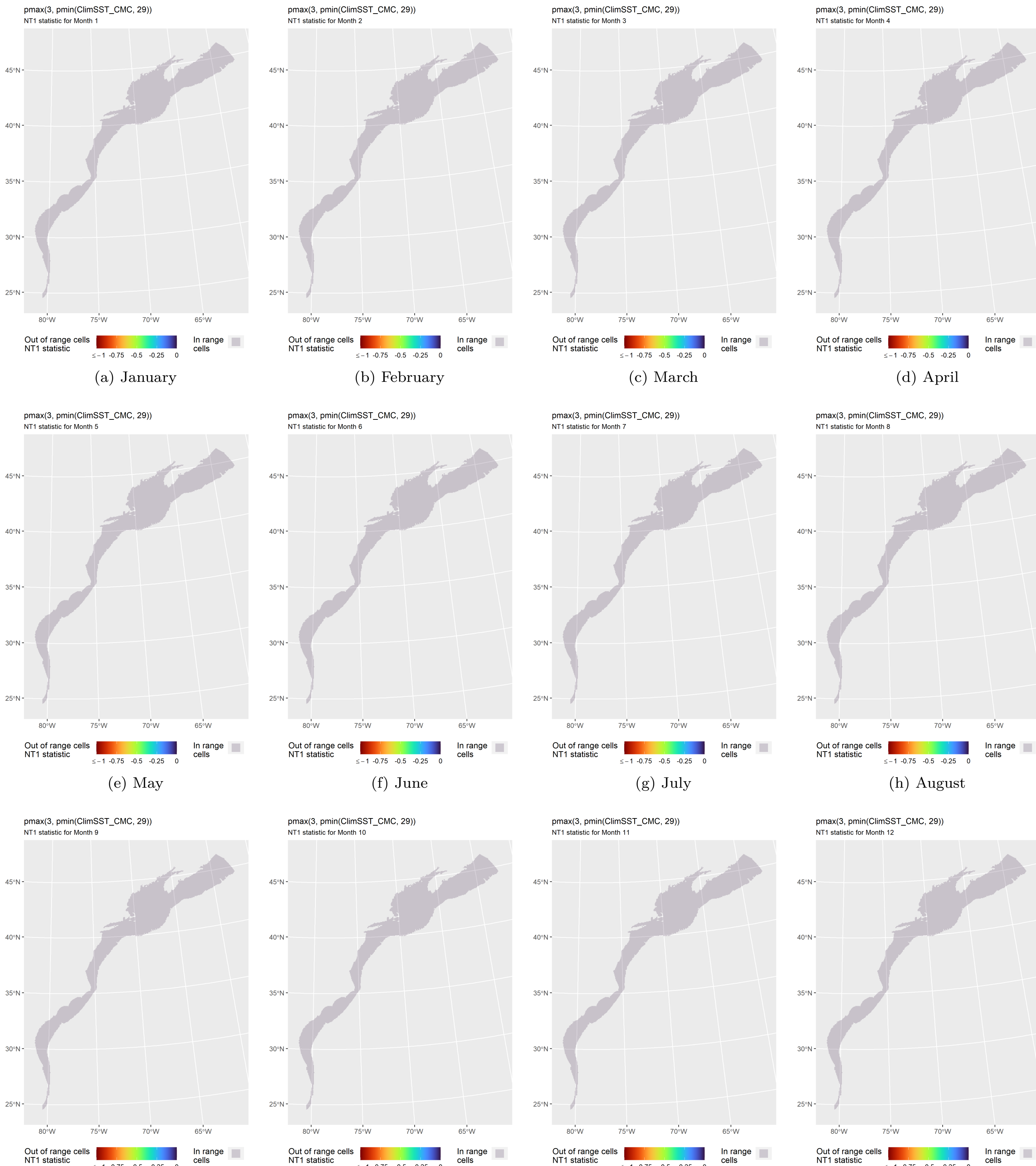


(k) November



(l) December

Figure 73: NT1 statistic (Mesgaran et al. (2014)) for the ClimSSS_HYCOM covariate in the model for the region Shallower than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there during the month. Areas within the sampled range appear in gray, indicating it did not occur.



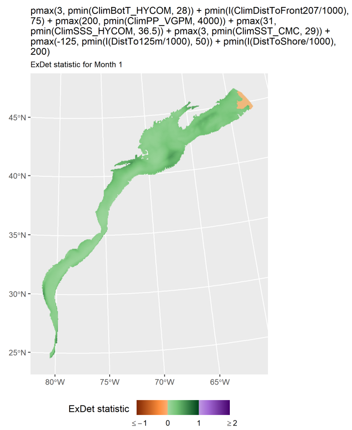
(a) January (b) February (c) March (d) April

(e) May (f) June (g) July (h) August

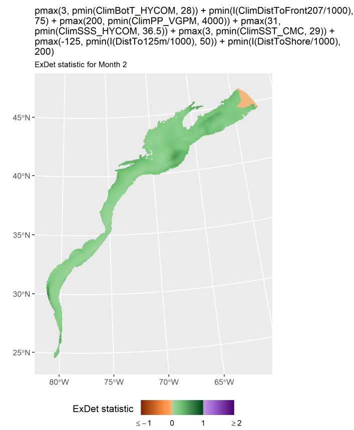
(i) September (j) October (k) November (l) December

Figure 74: NT1 statistic (Mesgaran et al. (2014)) for the ClimSST_CMC covariate in the model for the region Shallower than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there during the month. Areas within the sampled range appear in gray, indicating it did not occur.

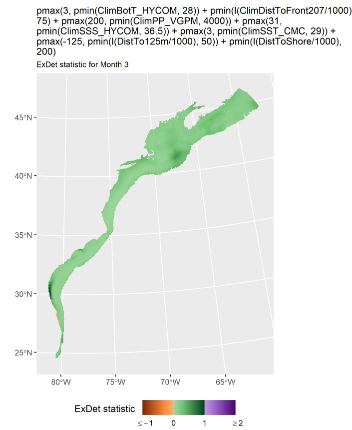
5.1.3.2 Multivariate Extrapolation



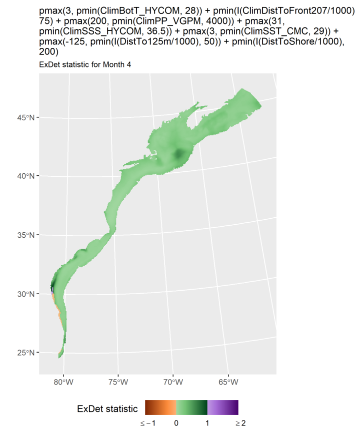
(a) January



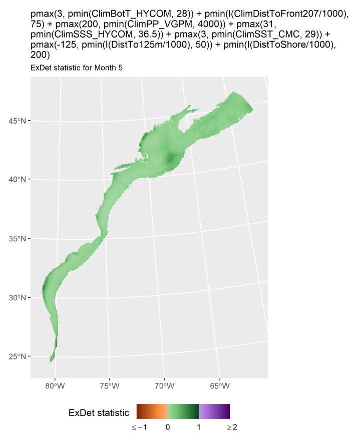
(b) February



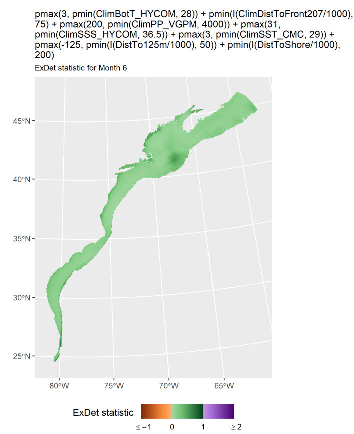
(c) March



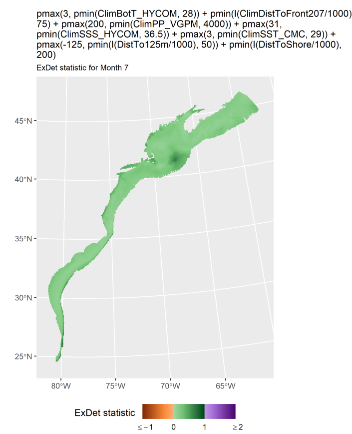
(d) April



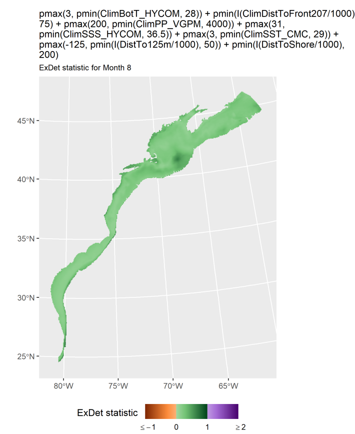
(e) May



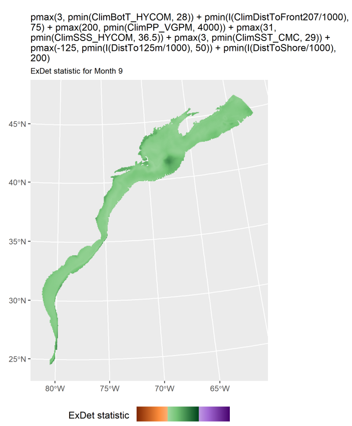
(f) June



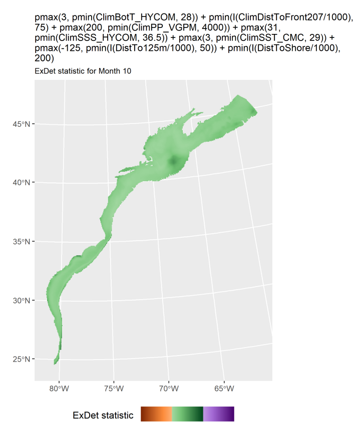
(g) July



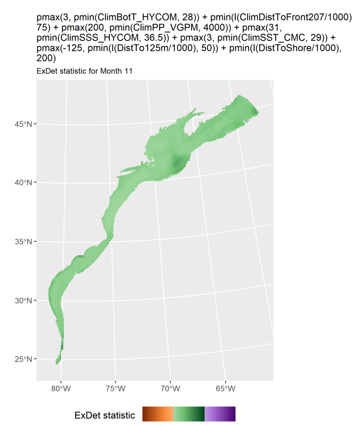
(h) August



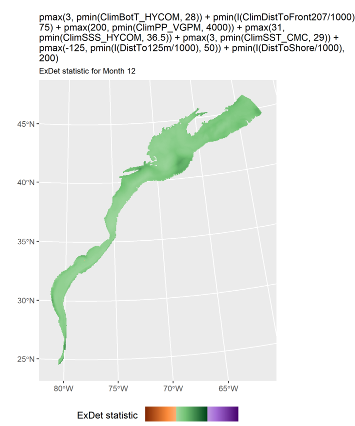
(i) September



(j) October



(k) November



(l) December

Figure 75: ExDet statistic (Mesgaran et al. (2014)) for all of the covariates used in the model for the region Shallower than 300m. Areas in orange (ExDet < 0) required univariate extrapolation of one or more covariates (see previous section). Areas in purple (ExDet > 1), did not require univariate extrapolation but did require multivariate extrapolation, by virtue of having novel combinations of covariates not represented in the survey data, according to the NT2 statistic (Mesgaran et al. (2014)). Areas in green ($0 \geq$ ExDet ≤ 1) did not require either type of extrapolation.

5.2 Offshore Model

About 200 sightings were available for this model, distributed beyond the shelf break between South Carolina and the Northeast Channel of the Gulf of Maine (Figure 76). For the same reasons as for the Shelf model (Section 5.1), we fitted a year-round model that incorporated all available survey data, rather than breaking the year into separate seasonal models.

The model selection procedure was straightforward. When ranked by REML score (Wood 2011), the highest ranked models with climatological covariates very slightly outranked those with contemporaneous covariates, explaining only 0.1% more deviance. Top models for both types of covariates predicted strong seasonal variability, but variability predicted by models with climatological covariates was extreme. Surveying beyond the shelf break was biased towards summer months and we lacked the data to substantiate the extreme drop in abundance predicted for offshore waters in winter and spring by the climatological-covariate model. The extant data showed sightings beyond the shelf break north of Cape Hatteras in every month except December and January. Therefore we selected the model with contemporaneous covariates as best.

The final model included five terms (Table 28). Functional relationships (Figure 79) showed a steady rise in density as either depth or sea surface temperature increased, corresponding to warm waters far offshore. The relationship with zooplankton biomass also showed a positive relationship, likely corresponding to higher values in the more productive waters north of the Gulf Stream, and an avoidance of the Blake Plateau, where no sightings were reported.

Relationships for the distance to SST fronts and and distance to mesoscale eddies covariates are harder to interpret. Most of the sightings occurred north of Cape Hatteras, within or north of the Gulf Stream, consistent with surveys that predated those used in our analysis, which reported sightings along the north wall of the Gulf Stream and warm-core eddies (Waring et al. 1992; Hayes et al. 2020), which are most common north of the Gulf Stream. The relationship with distance to fronts peaked at 15 km to fronts and fell steadily as distance increased, indicating higher density relatively close to fronts. The distance to eddies relationship was zero at a distance of zero, indicating no effect, then became slightly negative, indicating lower density, then turned positive in the range of 175-300 km from eddies, then became strongly negative, suggesting overall a complex pattern of density within 300 km of eddies and an avoidance of areas more than 300 km from eddies, such as the less dynamic edge of the Sargasso Sea in the southeast part of the study area. Finally, we caution that interpreting functional relationships in multi-covariate models is hard when the covariates are not fully independent effects, as is the case for models such as this one that utilize covariates derived from large-scale oceanographic processes.

5.2.1 Final Model

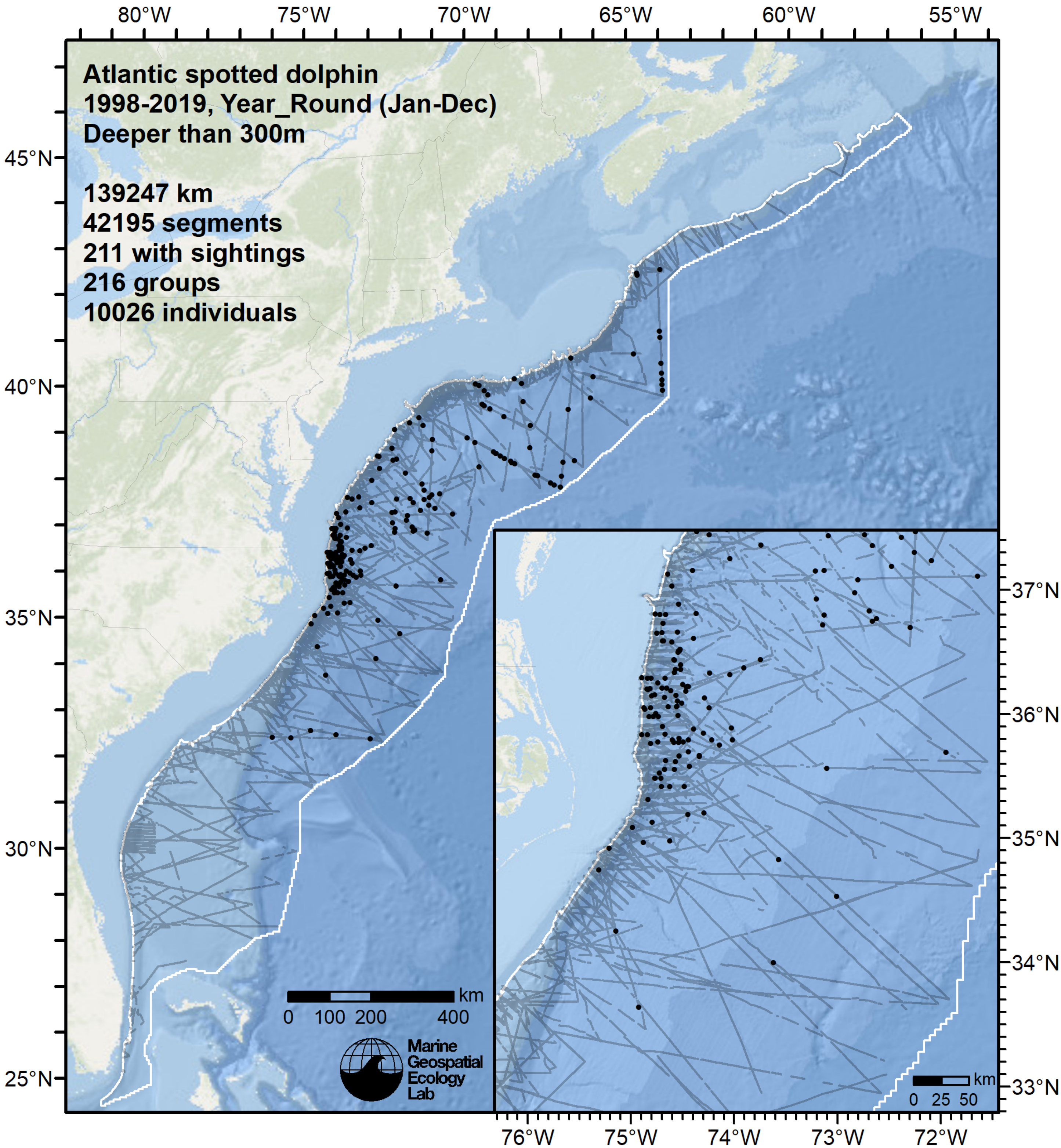


Figure 76: Survey segments used to fit the model for the region Deeper than 300m. Black points indicate segments with observations.

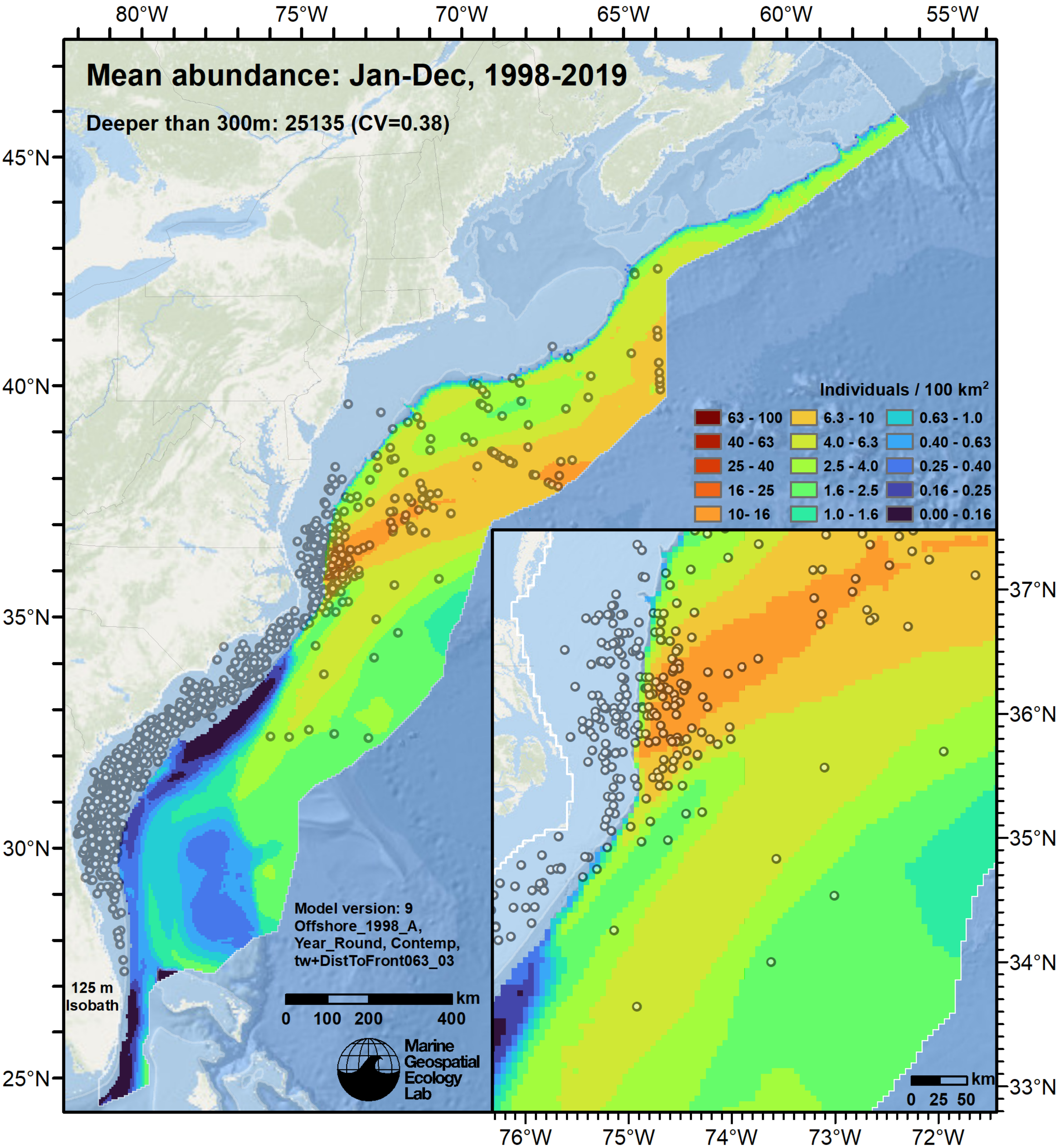


Figure 77: Atlantic spotted dolphin mean density for the indicated period, as predicted by the model for the region Deeper than 300m. Open circles indicate segments with observations. Mean total abundance and its coefficient of variation (CV) are given in the subtitle. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for seasonal and interannual variability in dynamic covariates.

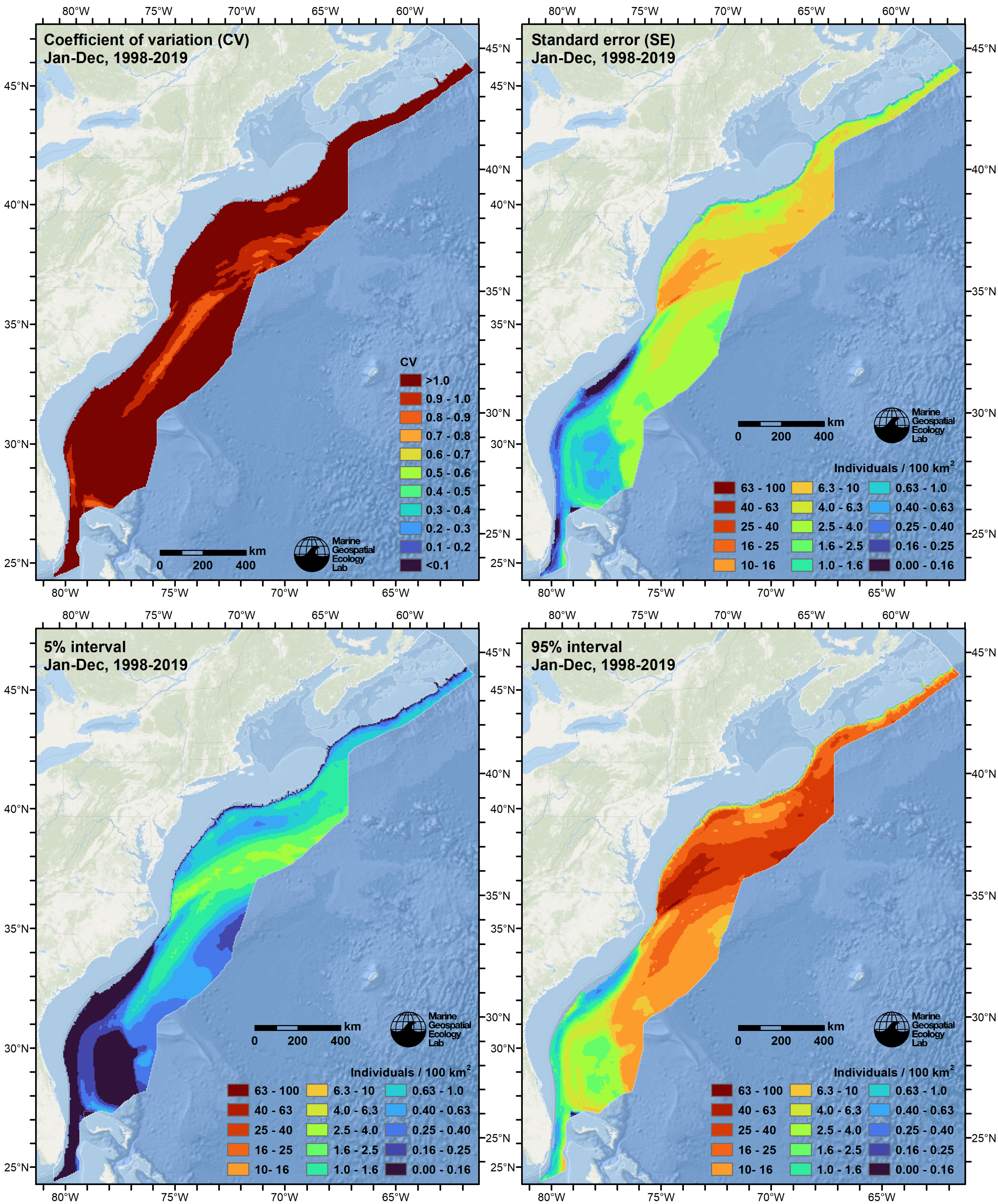
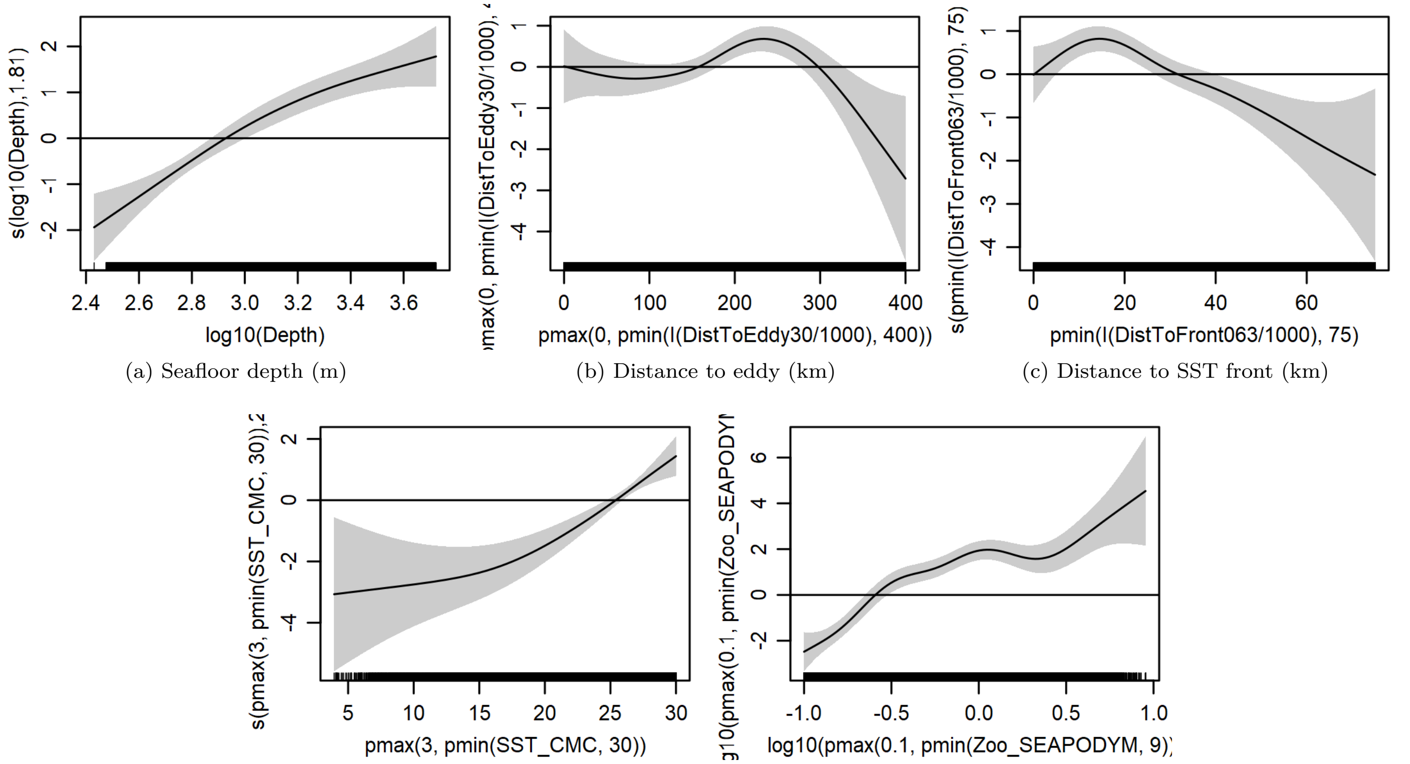


Figure 78: Uncertainty statistics for the Atlantic spotted dolphin mean density surface (Figure 77) predicted by the model for the region Deeper than 300m. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for seasonal and interannual variability in dynamic covariates.

Statistical output for this model:

```
Family: Tweedie(p=1.313)
Link function: log

Formula:
IndividualsCorrected ~ offset(log(SegmentArea)) + s(log10(Depth),
    bs = "ts") + s(pmax(3, pmin(SST_CMC, 30)), bs = "ts") + s(pmin(I(DistToFront063/1000),
    75), bs = "ts") + s(pmax(0, pmin(I(DistToEddy30/1000), 400)),
    bs = "ts") + s(log10(pmax(0.1, pmin(Zoo_SEAPODYM, 9))), bs = "ts")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -18.709      0.162  -115.5   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                                           edf Ref.df      F  p-value
s(log10(Depth))                          1.811      9  7.024  < 2e-16 ***
s(pmax(3, pmin(SST_CMC, 30)))            2.027      9  3.884  < 2e-16 ***
s(pmin(I(DistToFront063/1000), 75))      3.646      9  3.862  < 2e-16 ***
s(pmax(0, pmin(I(DistToEddy30/1000), 400))) 4.147      9  2.638 2.72e-05 ***
s(log10(pmax(0.1, pmin(Zoo_SEAPODYM, 9))))  5.516      9 12.137  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.0235   Deviance explained =   31%
-REML = 2159.4  Scale est. = 78.417    n = 42195

Method: REML   Optimizer: outer newton
full convergence after 10 iterations.
Gradient range [-4.360108e-05,7.572861e-06]
(score 2159.406 & scale 78.41675).
Hessian positive definite, eigenvalue range [0.3898487,820.9313].
Model rank =  46 / 46

Basis dimension (k) checking results. Low p-value (k-index<1) may
indicate that k is too low, especially if edf is close to k'.

                                           k'  edf k-index p-value
s(log10(Depth))                          9.00 1.81    0.64  <2e-16 ***
s(pmax(3, pmin(SST_CMC, 30)))            9.00 2.03    0.70   0.020 *
s(pmin(I(DistToFront063/1000), 75))      9.00 3.65    0.68   0.015 *
s(pmax(0, pmin(I(DistToEddy30/1000), 400))) 9.00 4.15    0.72   0.370
s(log10(pmax(0.1, pmin(Zoo_SEAPODYM, 9))))  9.00 5.52    0.68   0.015 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



(a) Seafloor depth (m)
(b) Distance to eddy (km)
(c) Distance to SST front (km)
(d) Sea surface temperature (°C)
(e) Zooplankton biomass (g C m^{-2})

Figure 79: Functional plots for the final model for the region Deeper than 300m. Transforms and other treatments are indicated in axis labels. *log10* indicates the covariate was $\log_{10}$ transformed. *pmax* and *pmin* indicate the covariate's minimum and maximum values, respectively, were Winsorized to the values shown. Winsorization was used to prevent runaway extrapolations during prediction when covariates exceeded sampled ranges, or for ecological reasons, depending on the covariate. */1000* indicates meters were transformed to kilometers for interpretation convenience.

Table 28: Covariates used in the final model for the region Deeper than 300m.

Covariate	Description
Depth	Depth (m) of the seafloor, from SRTM30_PLUS (Becker et al. (2009))
DistToEddy30	Monthly mean distance (km) to the edge of the closest mesoscale eddy of any polarity and at least 30 days old, derived with MGET (Roberts et al. (2010)) from the Aviso Mesoscale Eddy Trajectories Atlas (META2.0), produced by SSALTO/DUACS and distributed by AVISO+ (https://aviso.altimetry.fr) with support from CNES, in collaboration with Oregon State University with support from NASA, using the method of Schlax and Chelton (2016), based on Chelton et al. (2011)
DistToFront063	Monthly mean distance (km) to the closest sea surface temperature front detected in daily GHRSST Level 4 CMC0.2deg and CMC0.1deg images (Brasnett (2008); Canada Meteorological Center (2012); Meissner et al. (2016); Canada Meteorological Center (2016)) with MGET's implementation of the Canny edge detector (Roberts et al. (2010); Canny (1986))
SST_CMC	Monthly mean sea surface temperature (°C) from GHRSST Level 4 CMC0.2deg and CMC0.1deg (Brasnett (2008); Canada Meteorological Center (2012); Meissner et al. (2016); Canada Meteorological Center (2016))
Zoo_SEAPODYM	Monthly mean zooplankton biomass expressed in carbon (g C m^{-2}) from SEAPODYM (Lehodey et al. (2008); Lehodey et al. (2015)), provided by E.U. Copernicus Marine Service. doi: 10.48670/moi-00020

5.2.2 Diagnostic Plots

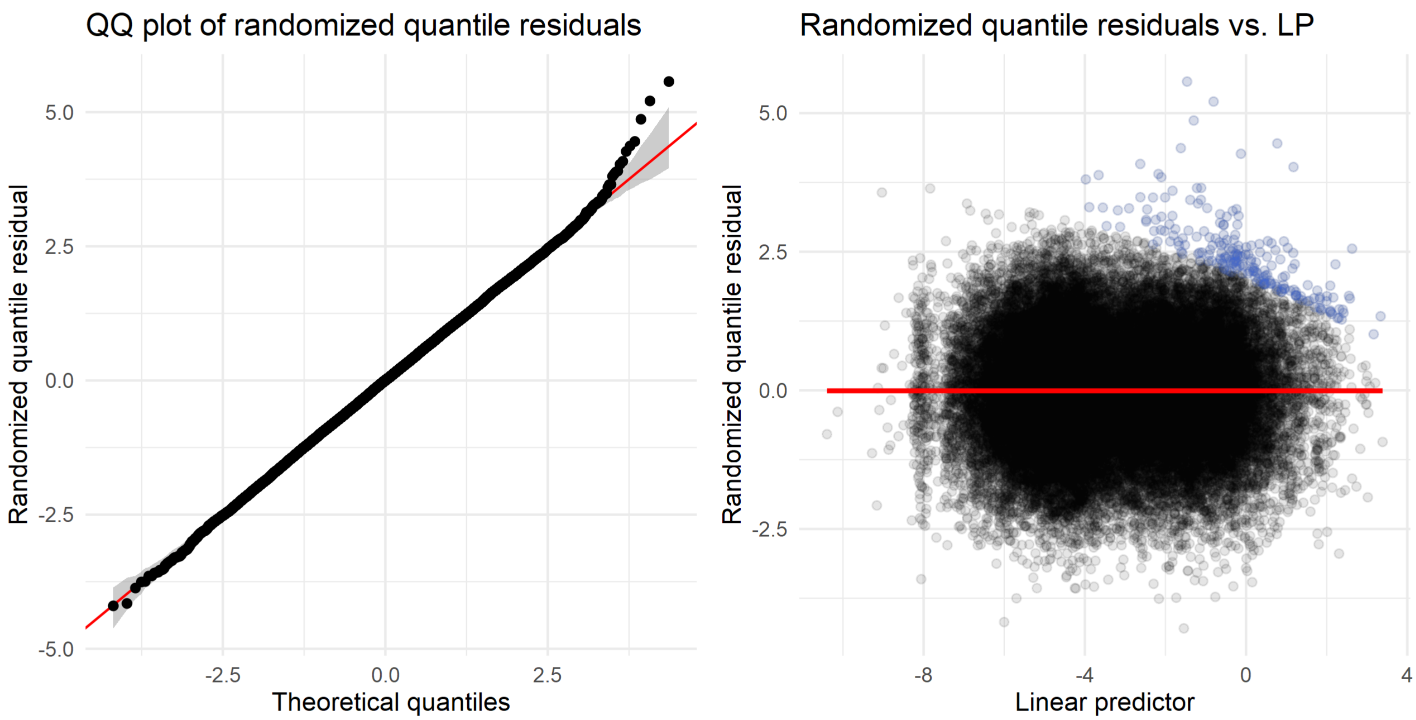


Figure 80: Residual plots for the final model for the region Deeper than 300m.

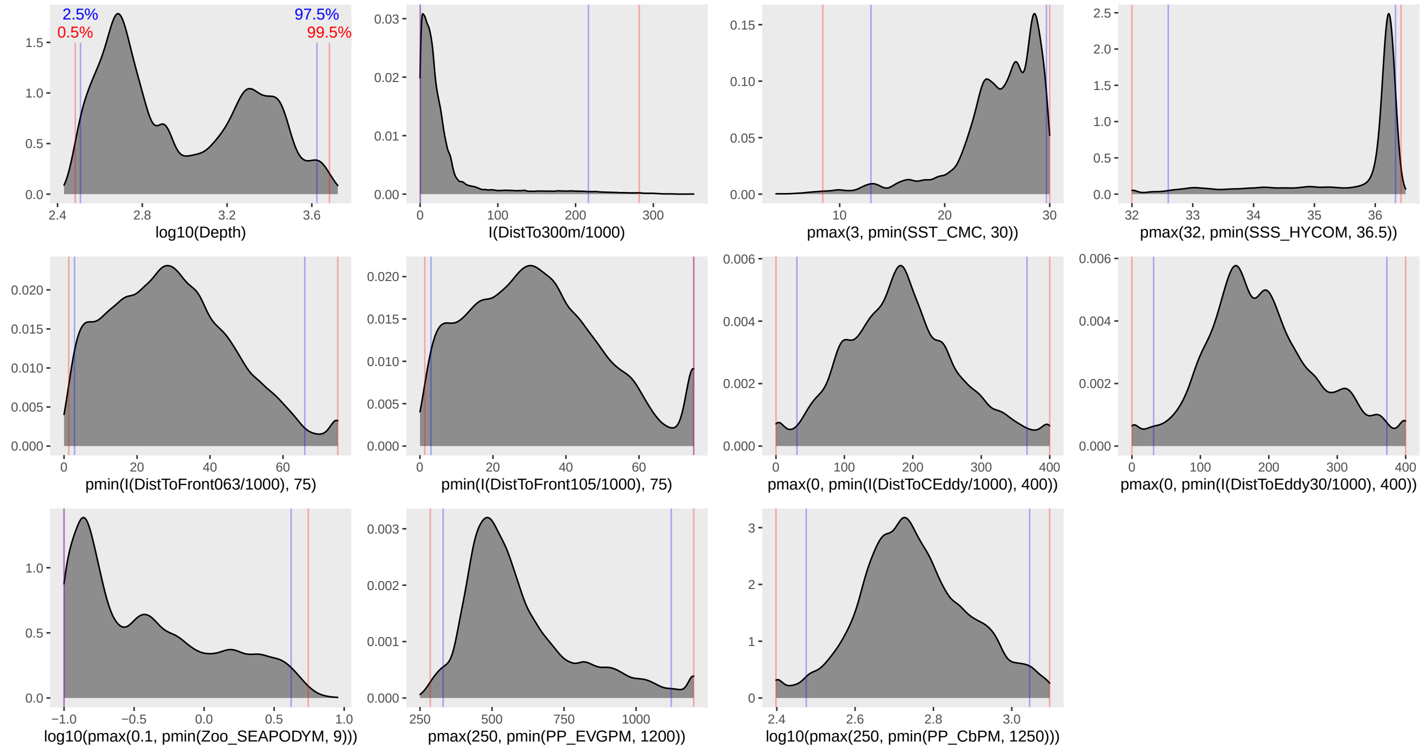


Figure 81: Density histograms showing the distributions of the covariates considered during the final model selection step. The final model may have included only a subset of the covariates shown here (see Figure 79), and additional covariates may have been considered in preceding selection steps. Red and blue lines enclose 99% and 95% of the distributions, respectively. Transforms and other treatments are indicated in axis labels. *log10* indicates the covariate was $\log_{10}$ transformed. *pmax* and *pmin* indicate the covariate's minimum and maximum values, respectively, were Winsorized to the values shown. Winsorization was used to prevent runaway extrapolations during prediction when covariates exceeded sampled ranges, or for ecological reasons, depending on the covariate. */1000* indicates meters were transformed to kilometers for interpretation convenience.

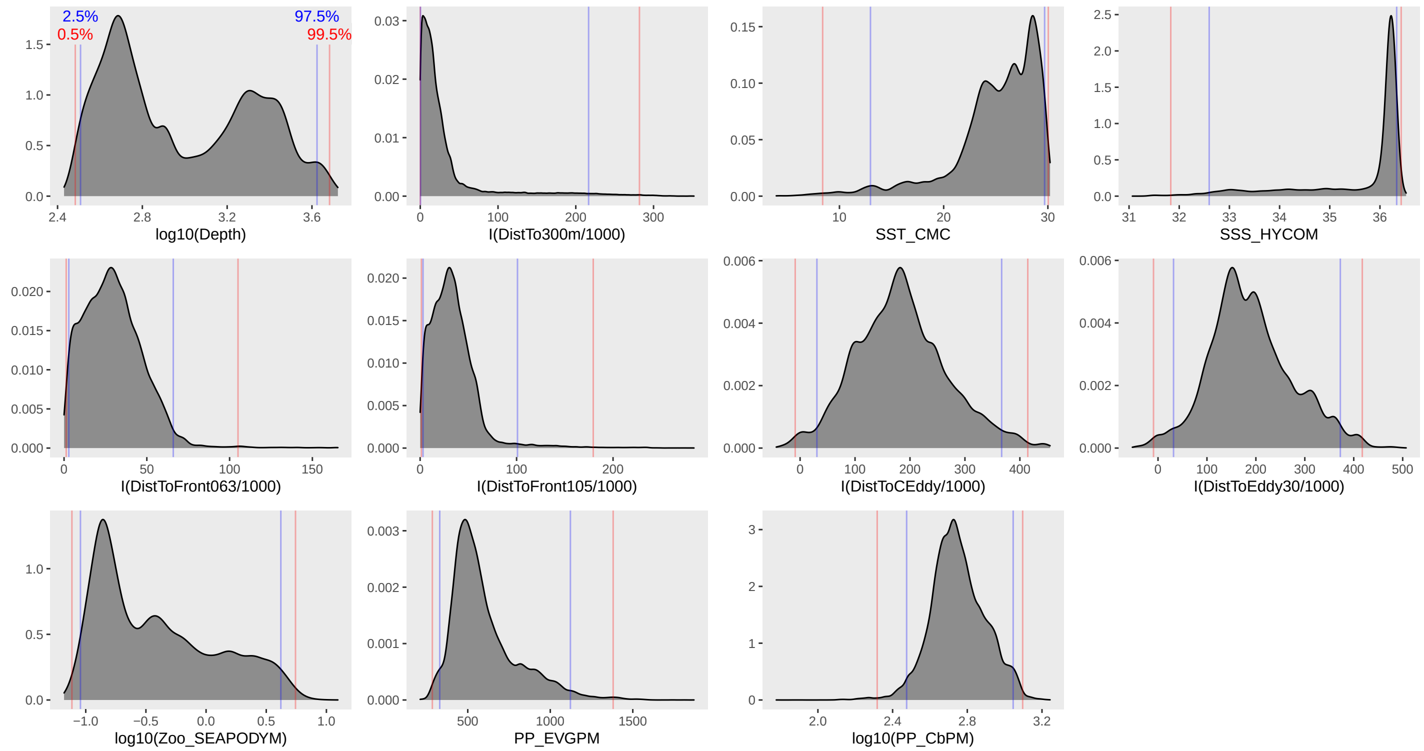


Figure 82: Density histograms shown in Figure 81 replotted without Winsorization, to show the full range of sampling represented by survey segments.

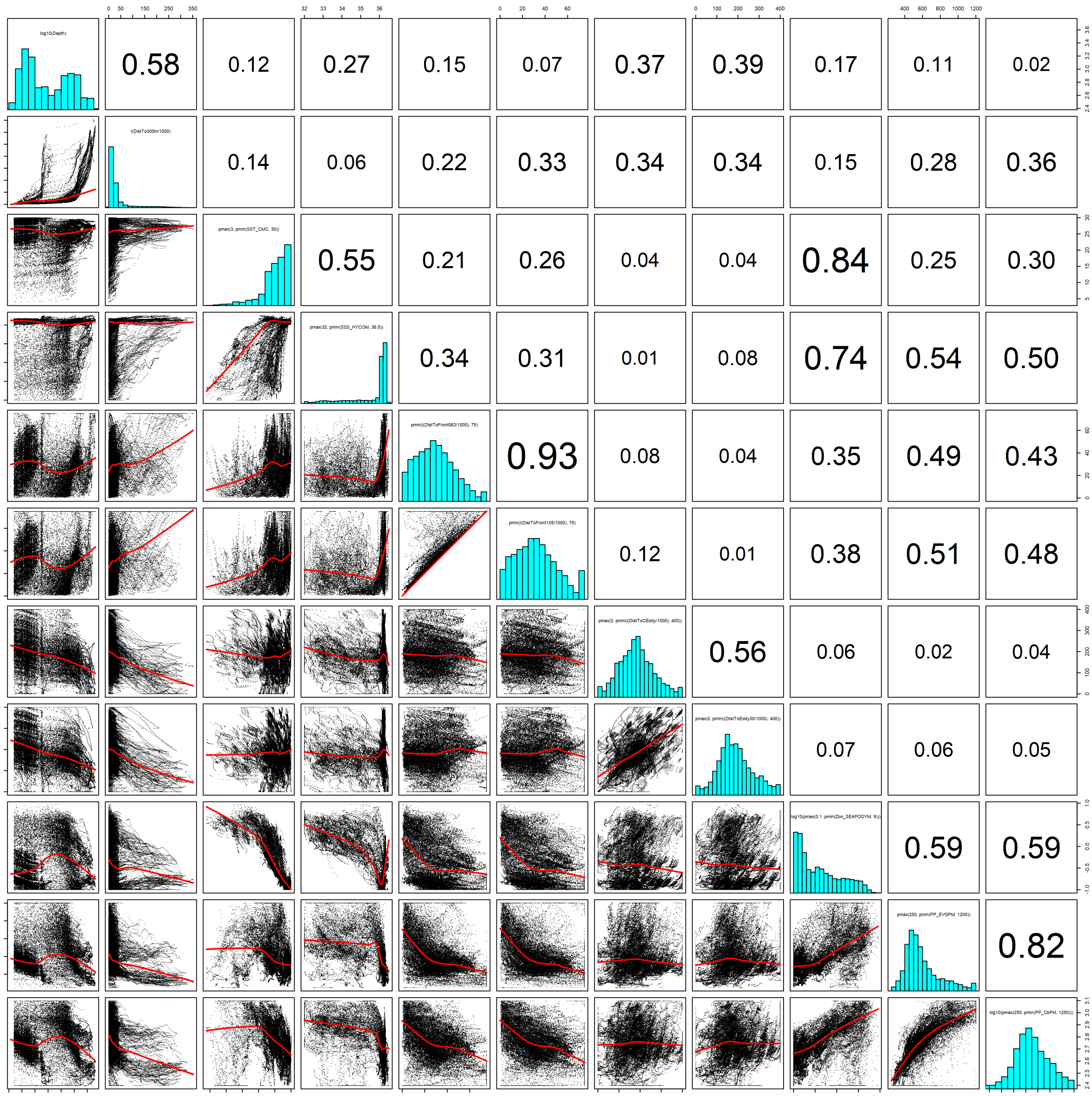


Figure 83: Scatterplot matrix of the covariates considered during the final model selection step. The final model may have included only a subset of the covariates shown here (see Figure 79), and additional covariates may have been considered in preceding selection steps. Covariates are transformed and Winsorized as shown in Figure 81. This plot is used to check simple correlations between covariates (via pairwise Pearson coefficients above the diagonal) and visually inspect for concurvity (via scatterplots and red lowess curves below the diagonal).

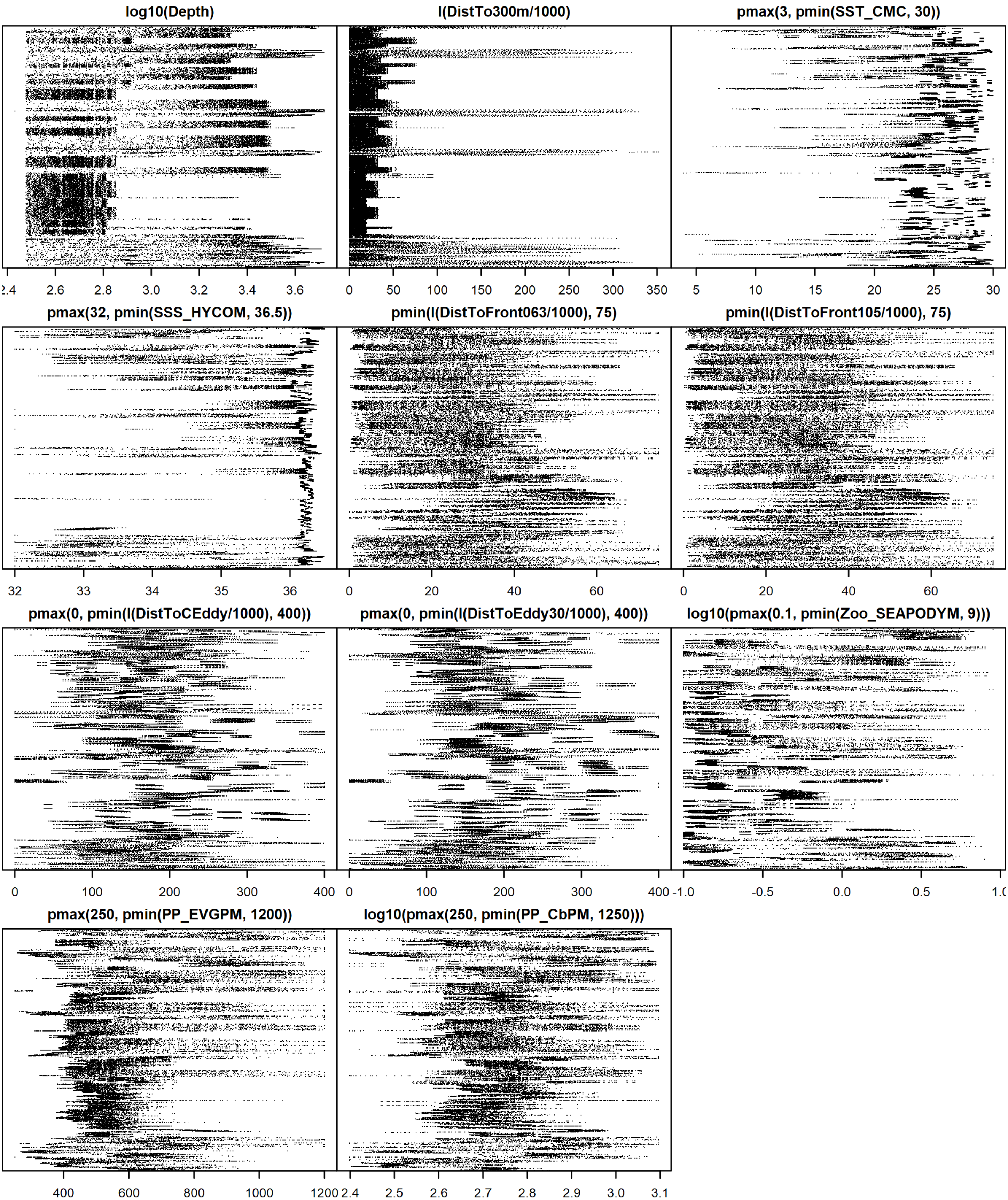


Figure 84: Dotplot of the covariates considered during the final model selection step. The final model may have included only a subset of the covariates shown here (see Figure 79), and additional covariates may have been considered in preceding selection steps. Covariates are transformed and Winsorized as shown in Figure 81. This plot is used to check for suspicious patterns and outliers in the data. Points are ordered vertically by segment ID, sequentially in time.

5.2.3 Extrapolation Diagnostics

5.2.3.1 Univariate Extrapolation

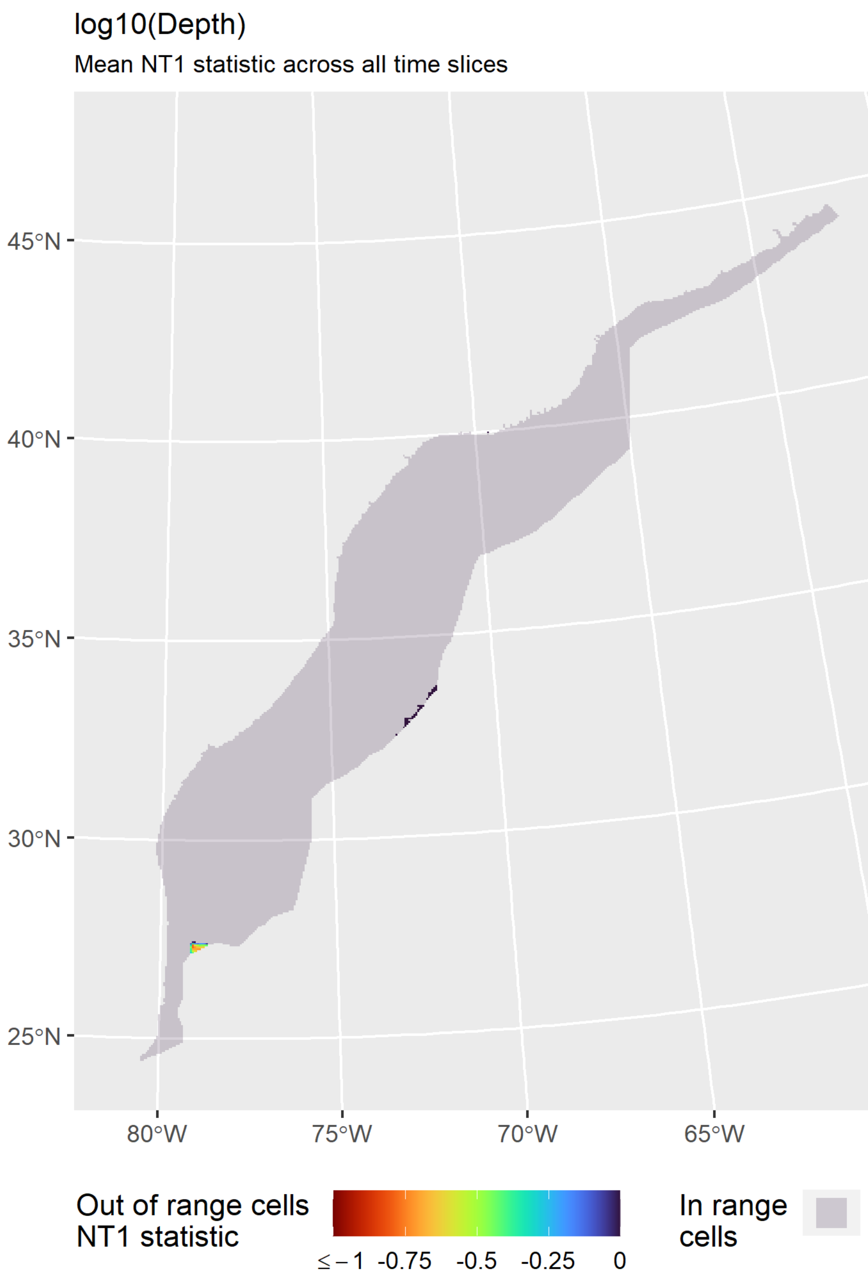
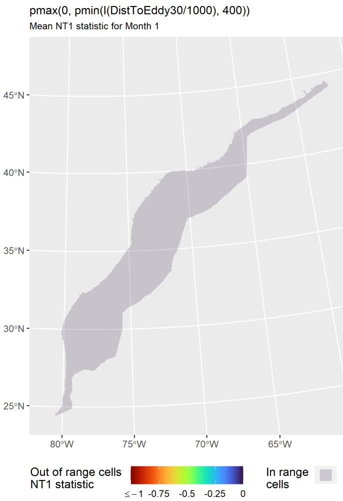
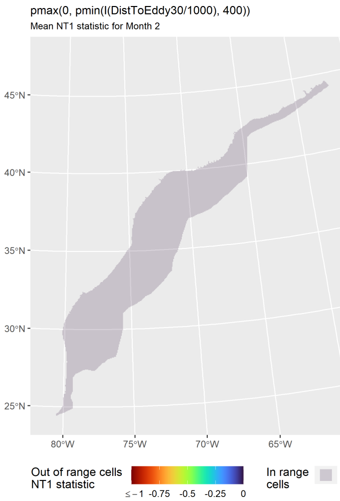


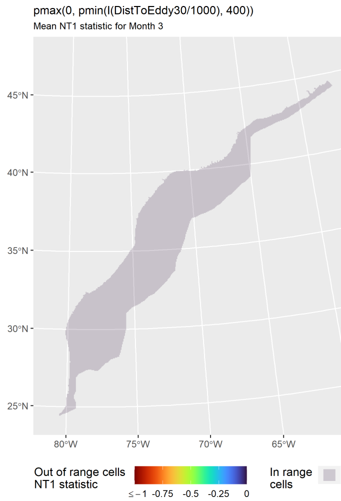
Figure 85: NT1 statistic (Mesgaran et al. (2014)) for static covariates used in the model for the region Deeper than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there. Areas within the sampled range appear in gray, indicating it did not occur.



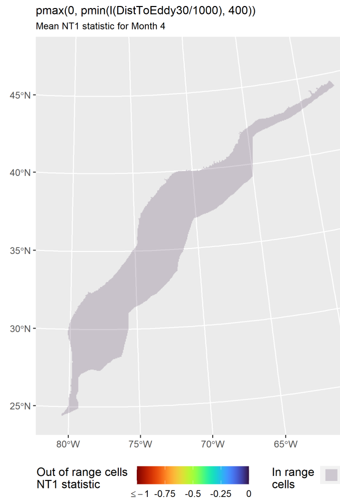
(a) January



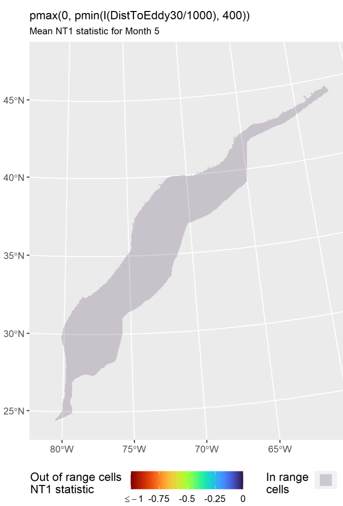
(b) February



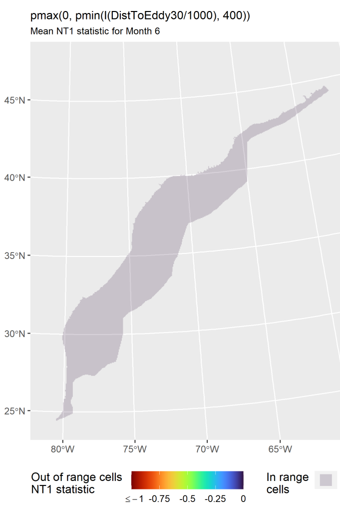
(c) March



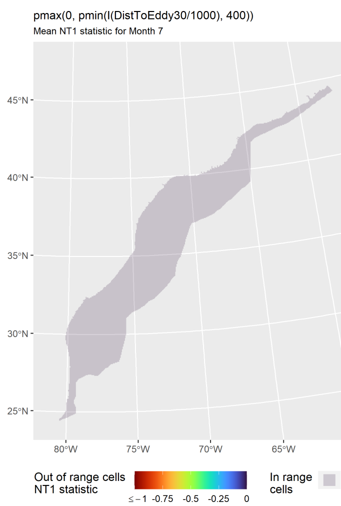
(d) April



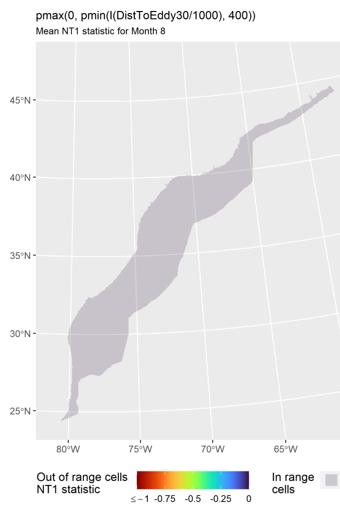
(e) May



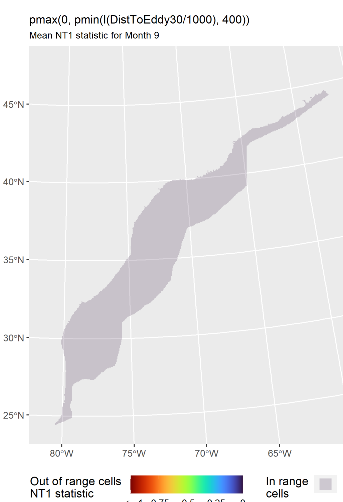
(f) June



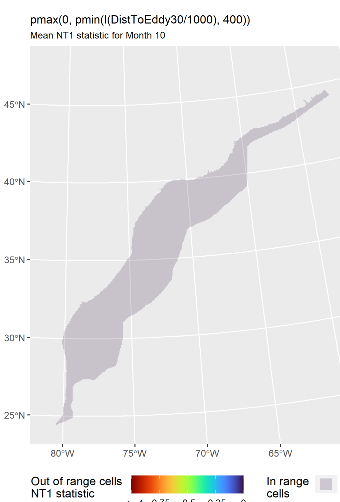
(g) July



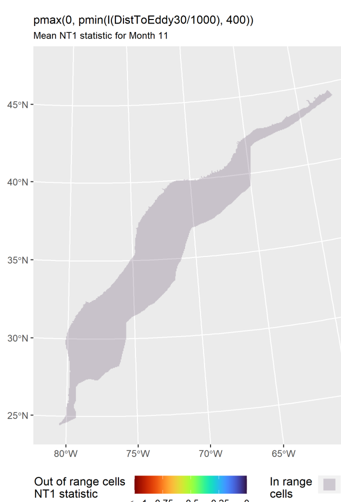
(h) August



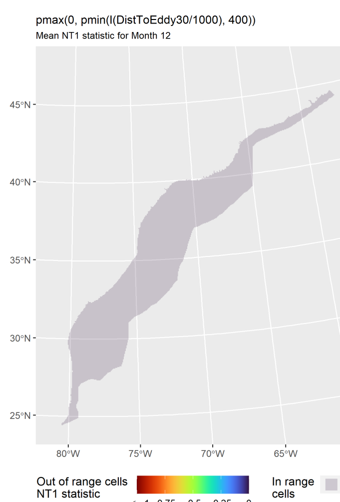
(i) September



(j) October

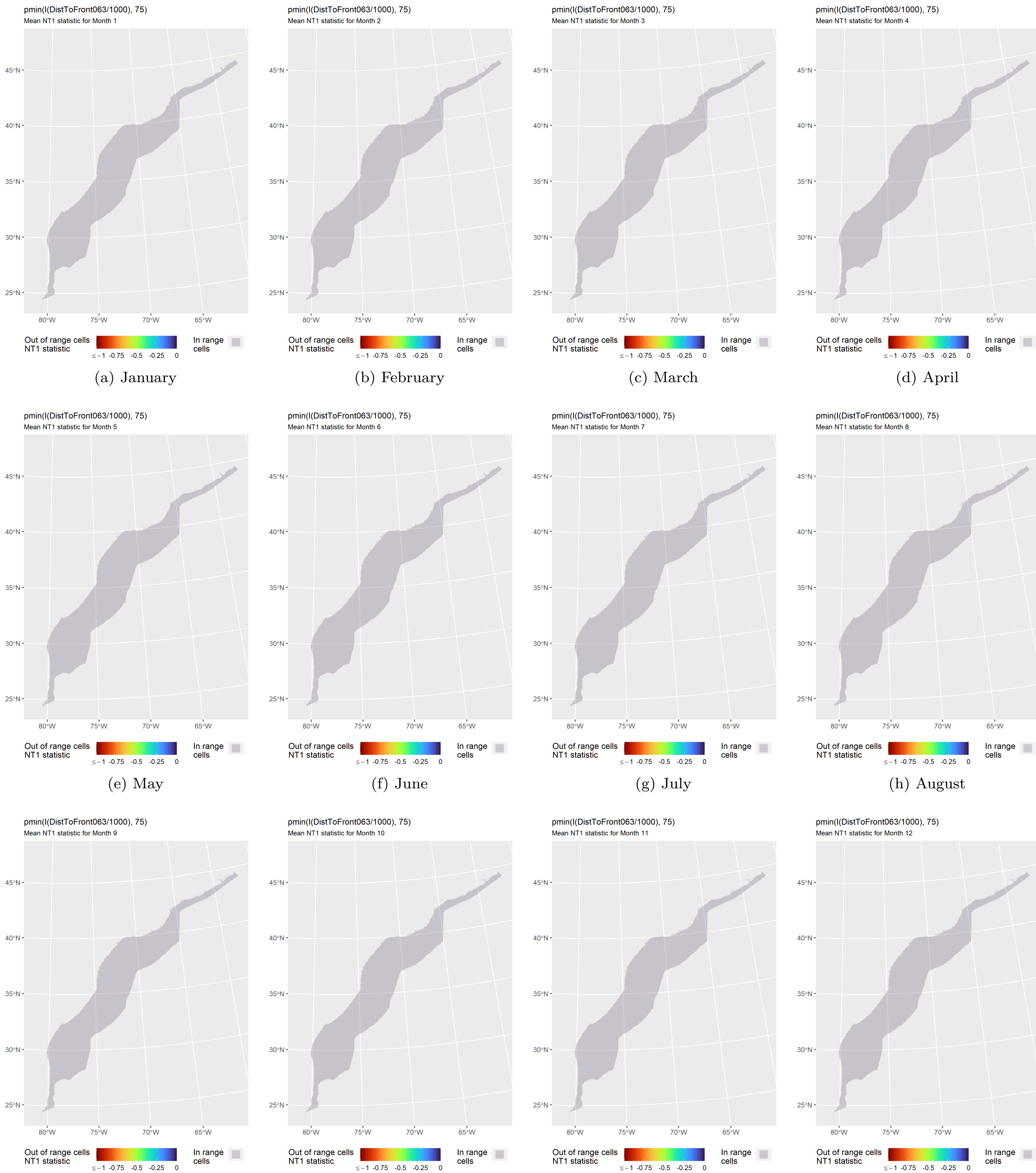


(k) November



(l) December

Figure 86: NT1 statistic (Mesgaran et al. (2014)) for the DistToEddy30 covariate in the model for the region Deeper than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there during the month. Areas within the sampled range appear in gray, indicating it did not occur.

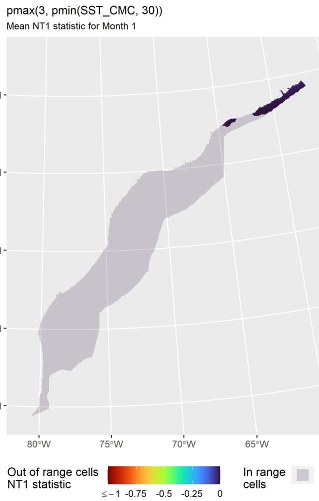


(a) January (b) February (c) March (d) April

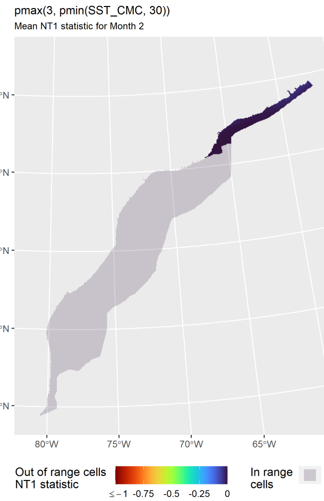
(e) May (f) June (g) July (h) August

(i) September (j) October (k) November (l) December

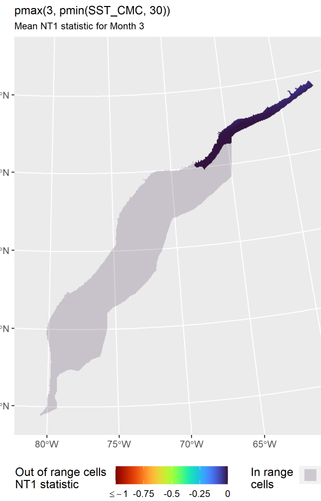
Figure 87: NT1 statistic (Mesgaran et al. (2014)) for the DistToFront063 covariate in the model for the region Deeper than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there during the month. Areas within the sampled range appear in gray, indicating it did not occur.



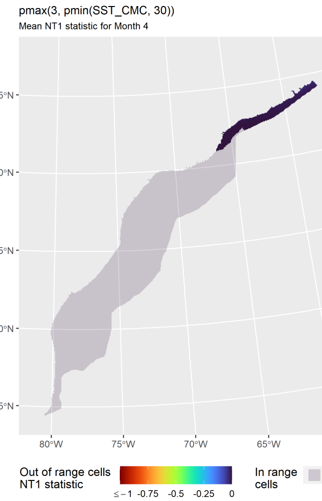
(a) January



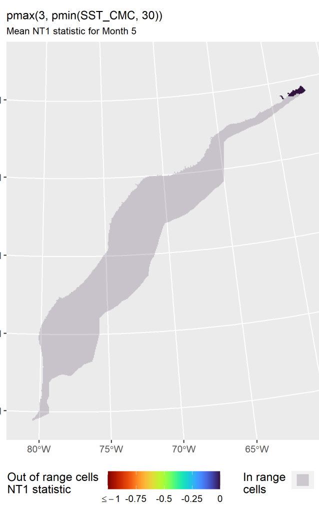
(b) February



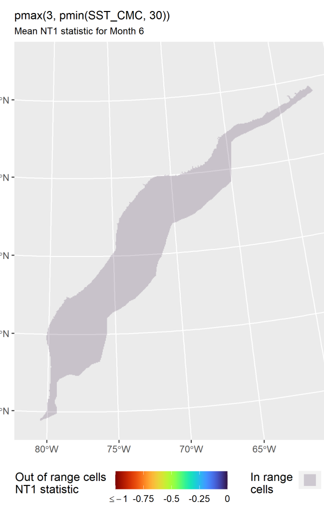
(c) March



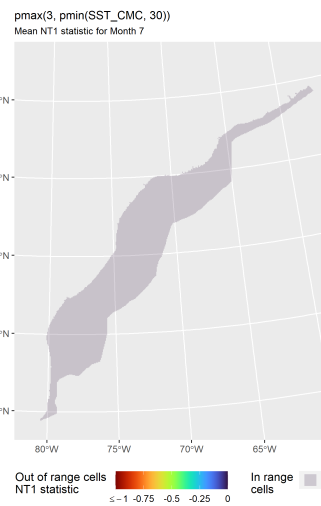
(d) April



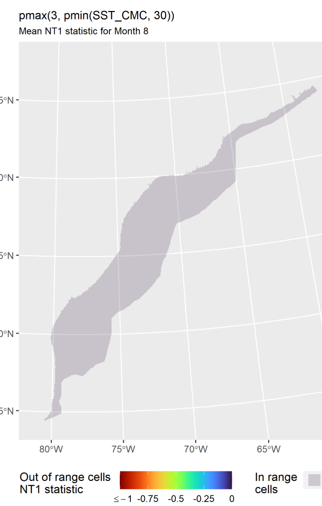
(e) May



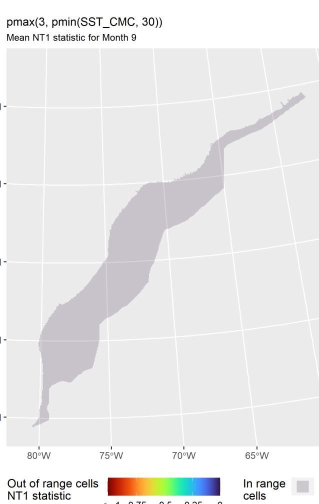
(f) June



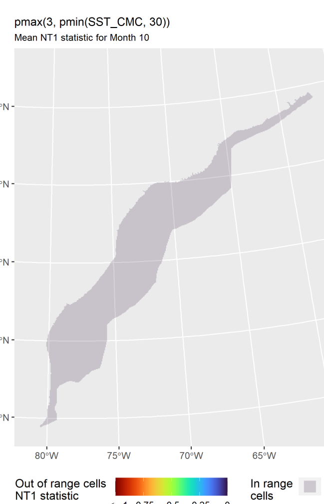
(g) July



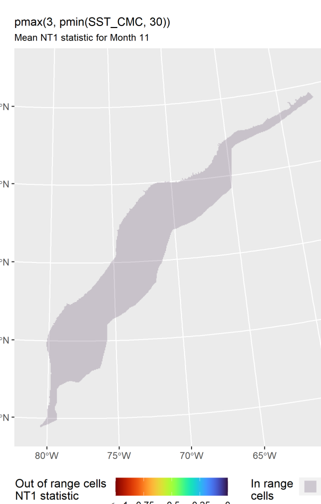
(h) August



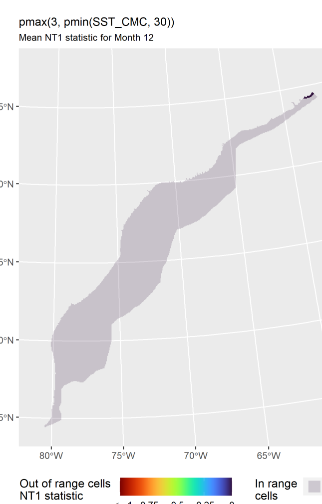
(i) September



(j) October

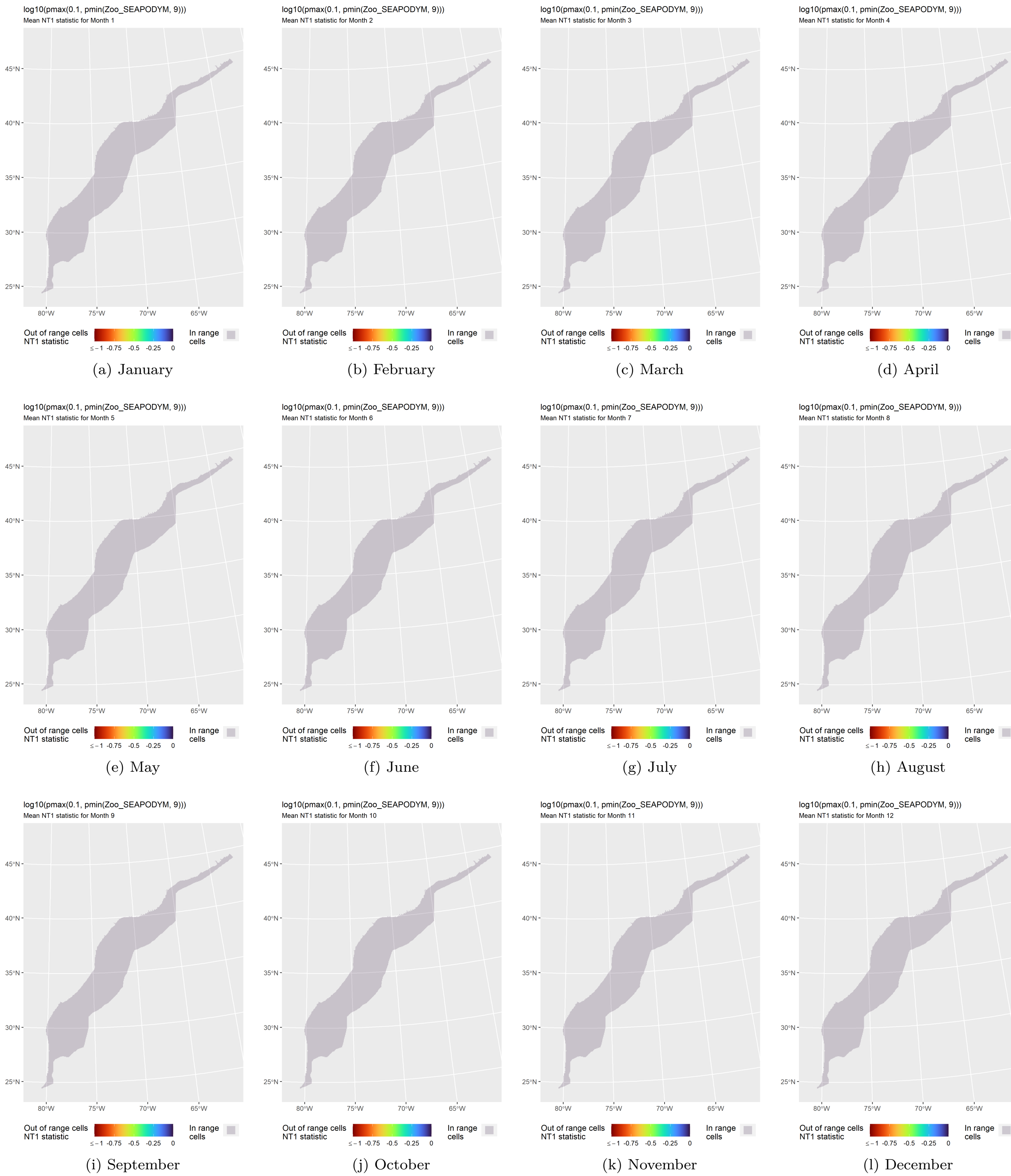


(k) November



(l) December

Figure 88: NT1 statistic (Mesgaran et al. (2014)) for the SST_CMC covariate in the model for the region Deeper than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there during the month. Areas within the sampled range appear in gray, indicating it did not occur.



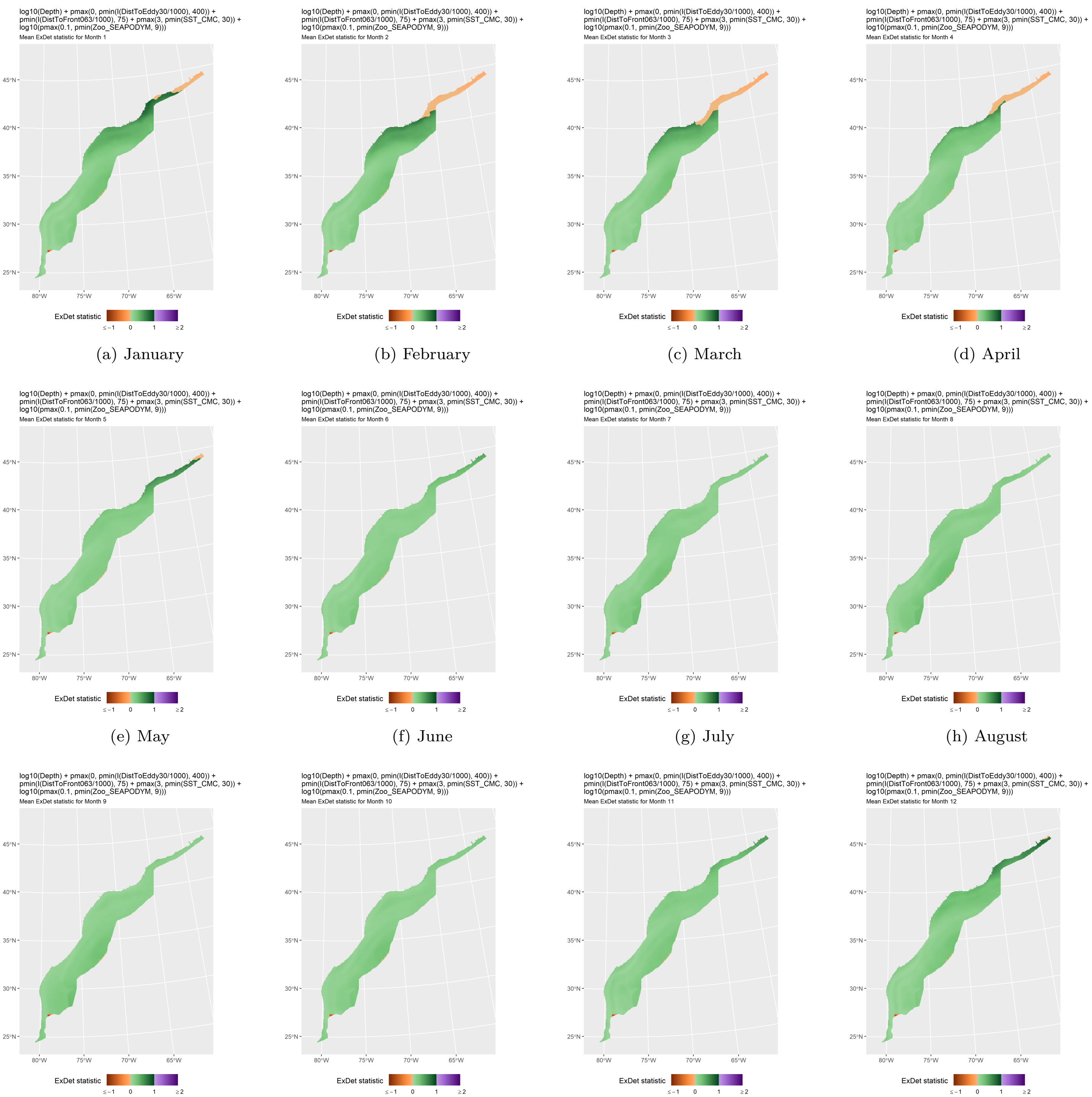
(a) January (b) February (c) March (d) April

(e) May (f) June (g) July (h) August

(i) September (j) October (k) November (l) December

Figure 89: NT1 statistic (Mesgaran et al. (2014)) for the Zoo_SEAPODYM covariate in the model for the region Deeper than 300m. Areas outside the sampled range of a covariate appear in color, indicating univariate extrapolation of that covariate occurred there during the month. Areas within the sampled range appear in gray, indicating it did not occur.

5.2.3.2 Multivariate Extrapolation



(a) January (b) February (c) March (d) April

(e) May (f) June (g) July (h) August

(i) September (j) October (k) November (l) December

Figure 90: ExDet statistic (Mesgaran et al. (2014)) for all of the covariates used in the model for the region Deeper than 300m. Areas in orange (ExDet < 0) required univariate extrapolation of one or more covariates (see previous section). Areas in purple (ExDet > 1), did not require univariate extrapolation but did require multivariate extrapolation, by virtue of having novel combinations of covariates not represented in the survey data, according to the NT2 statistic (Mesgaran et al. (2014)). Areas in green ($0 \geq$ ExDet ≤ 1) did not require either type of extrapolation.

6 Predictions

Based on our evaluation of this model in the context of what is known of this species, we summarized the "Shelf" model's predictions into monthly climatological density and uncertainty surfaces, but the "Offshore" into single, year-round surfaces rather than monthly surfaces. The maps below will therefore show variability on the shelf from month to month but a static prediction offshore. Please see Section 7 for discussion of this decision.

6.1 Summarized Predictions

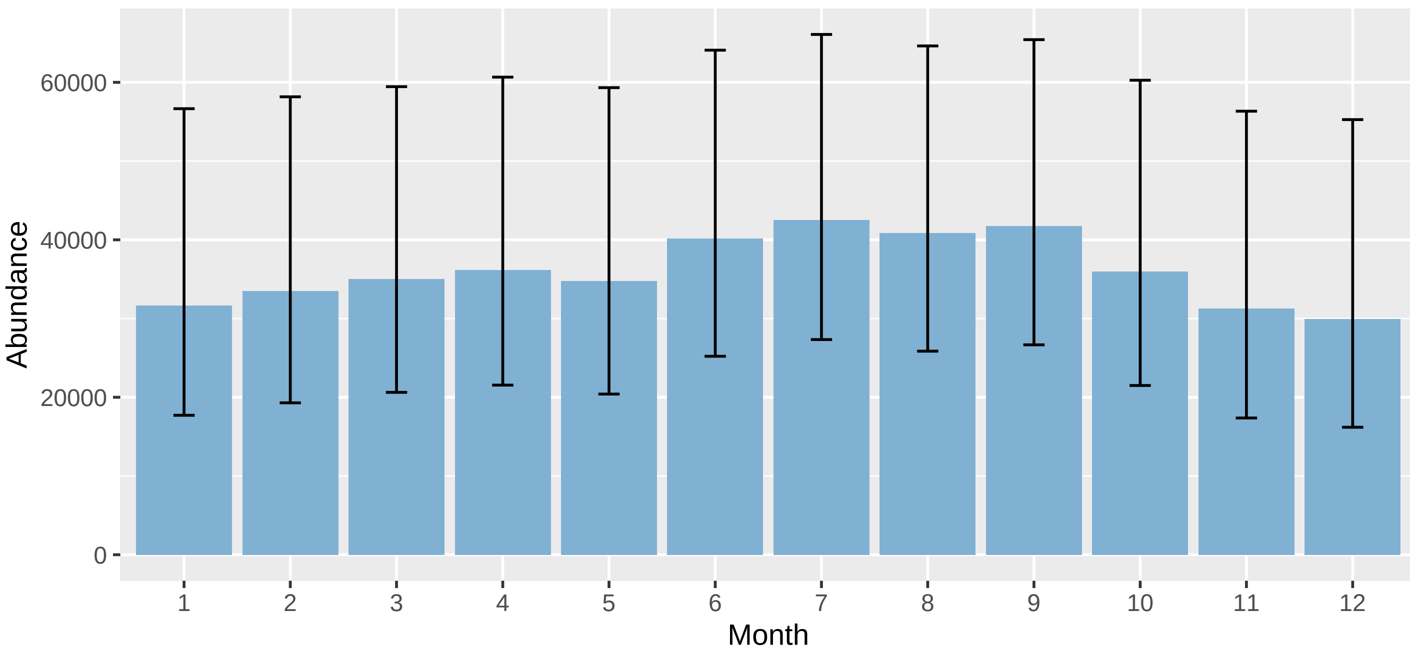


Figure 91: Mean monthly abundance for the prediction area for 1998-2019. Error bars are a 95% interval, made with a log-normal approximation using the prediction's CV. The CV was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

Table 29: Mean monthly abundance and density for the prediction area for 1998-2019. CV and intervals estimated as described for the previous figure.

Month	Abundance	CV	95% Interval	Area (km^2)	Density (individuals / 100 km^2)
1	31,677	0.303	17,711 - 56,654	1,273,050	2.49
2	33,500	0.287	19,295 - 58,162	1,273,050	2.63
3	35,017	0.275	20,626 - 59,451	1,273,050	2.75
4	36,150	0.269	21,543 - 60,660	1,273,050	2.84
5	34,792	0.277	20,405 - 59,324	1,273,050	2.73
6	40,191	0.241	25,206 - 64,084	1,273,050	3.16
7	42,495	0.228	27,327 - 66,081	1,273,050	3.34
8	40,876	0.237	25,855 - 64,625	1,273,050	3.21
9	41,764	0.232	26,661 - 65,420	1,273,050	3.28
10	35,992	0.268	21,494 - 60,268	1,273,050	2.83
11	31,279	0.307	17,367 - 56,336	1,273,050	2.46
12	29,915	0.321	16,193 - 55,265	1,273,050	2.35

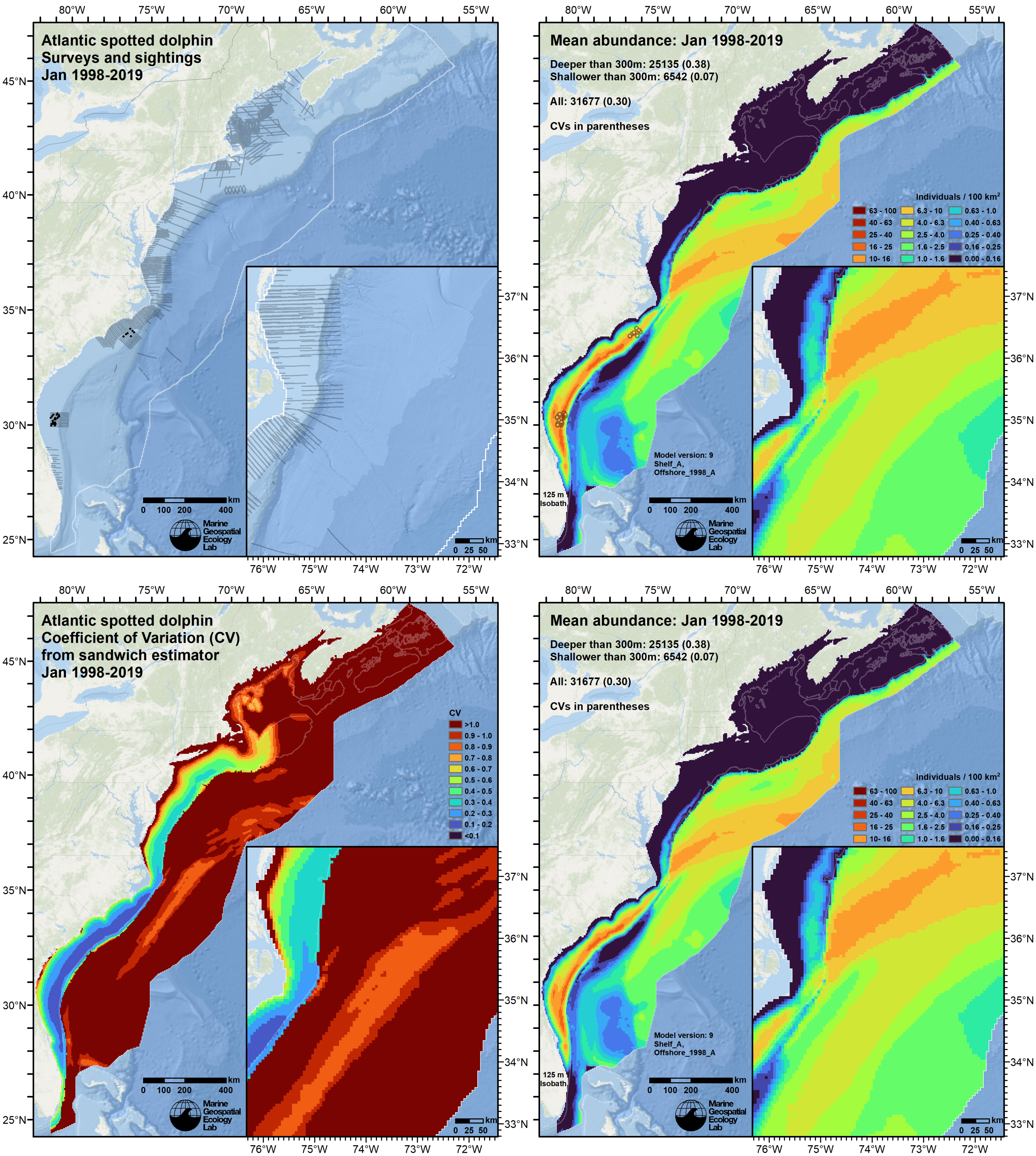


Figure 92: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of January for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

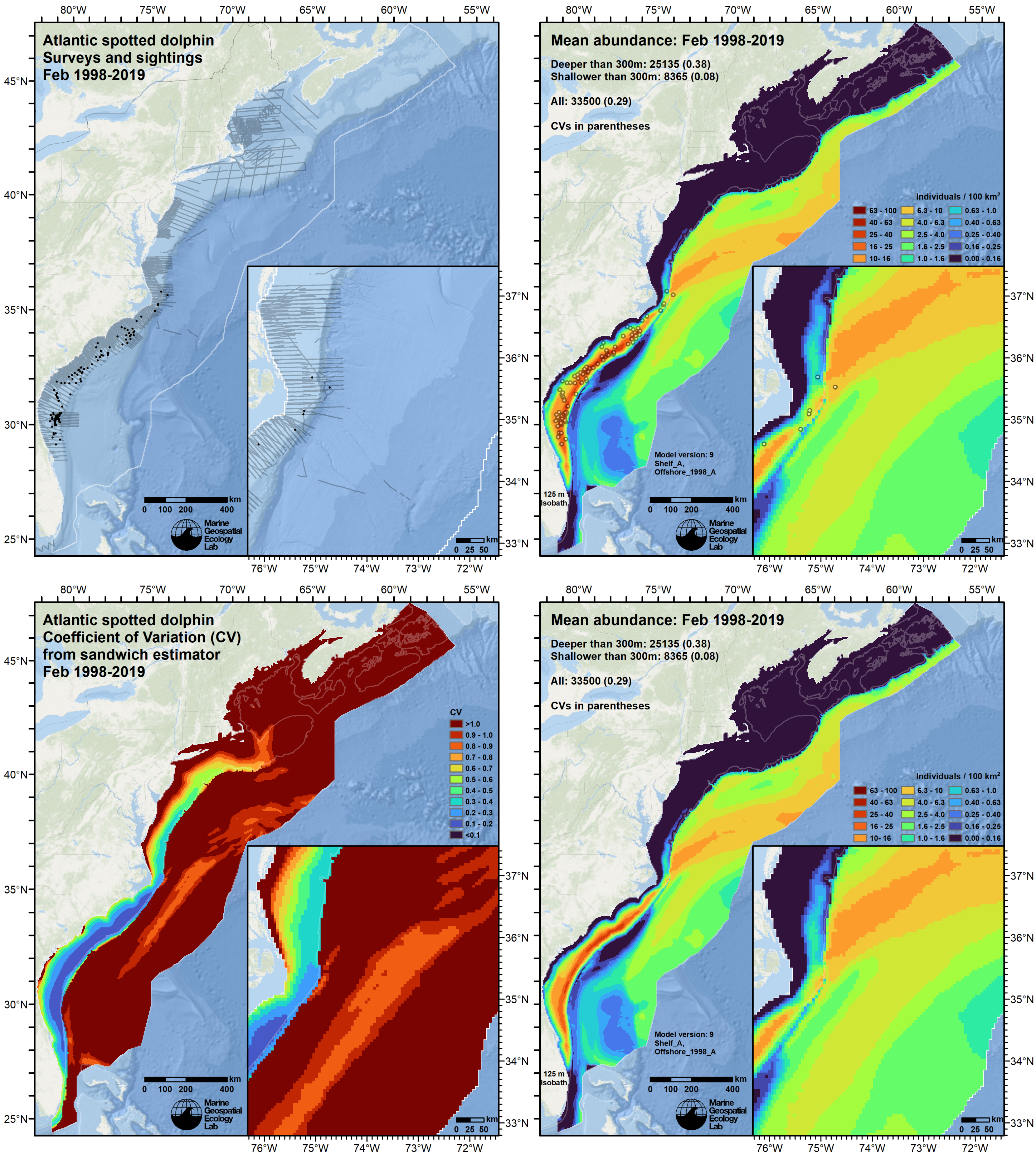


Figure 93: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of February for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

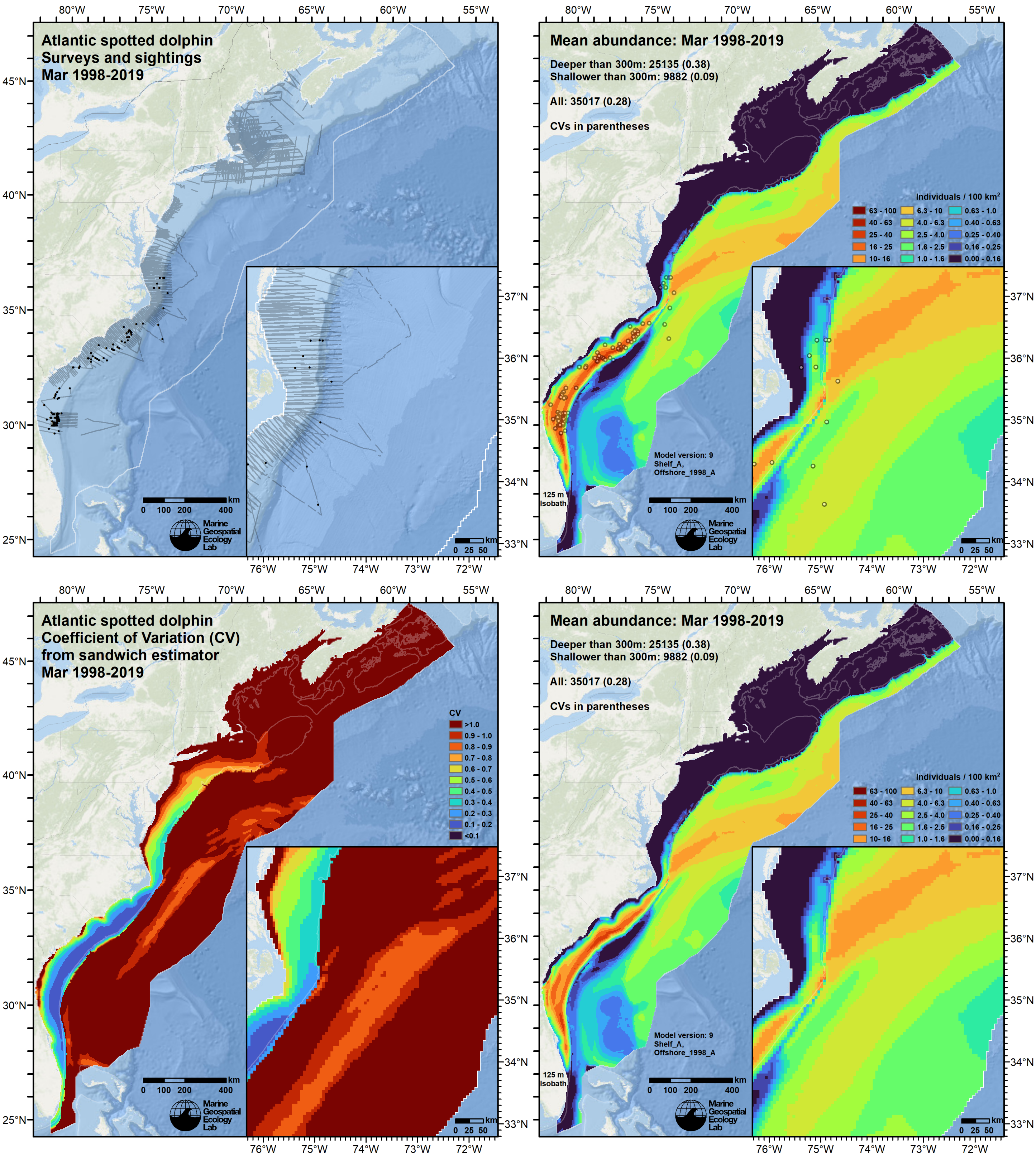


Figure 94: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of March for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

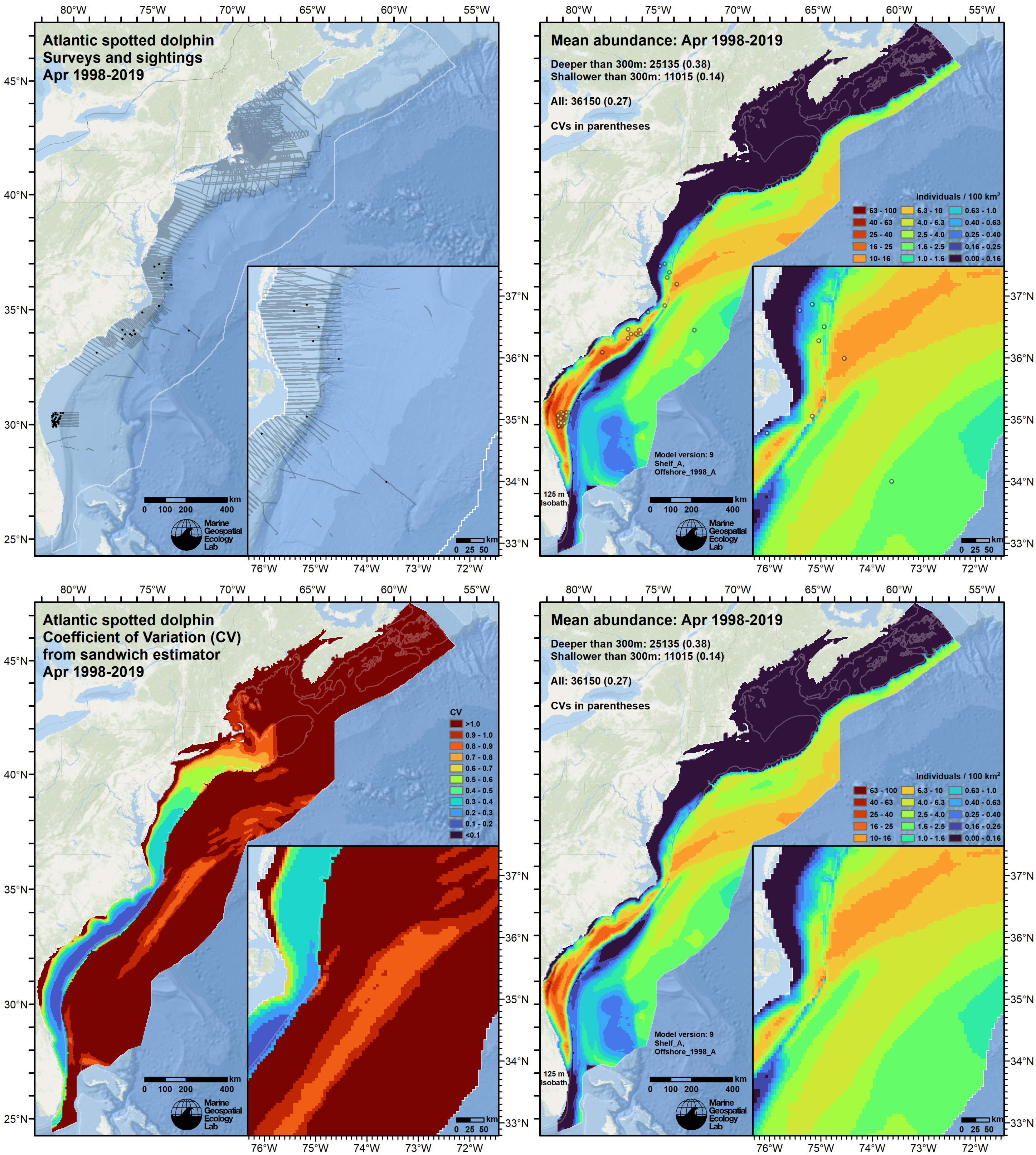


Figure 95: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of April for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

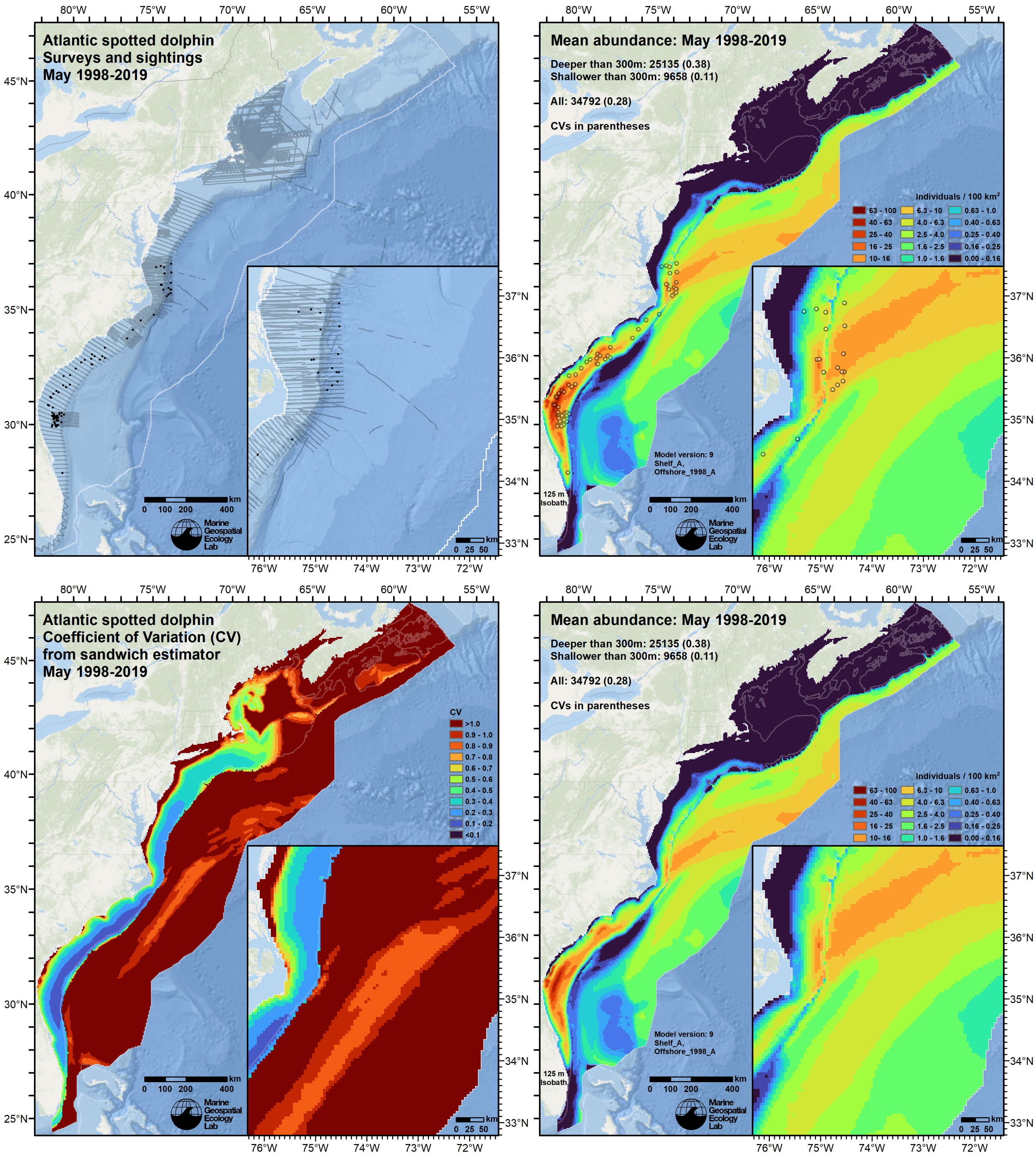


Figure 96: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of May for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

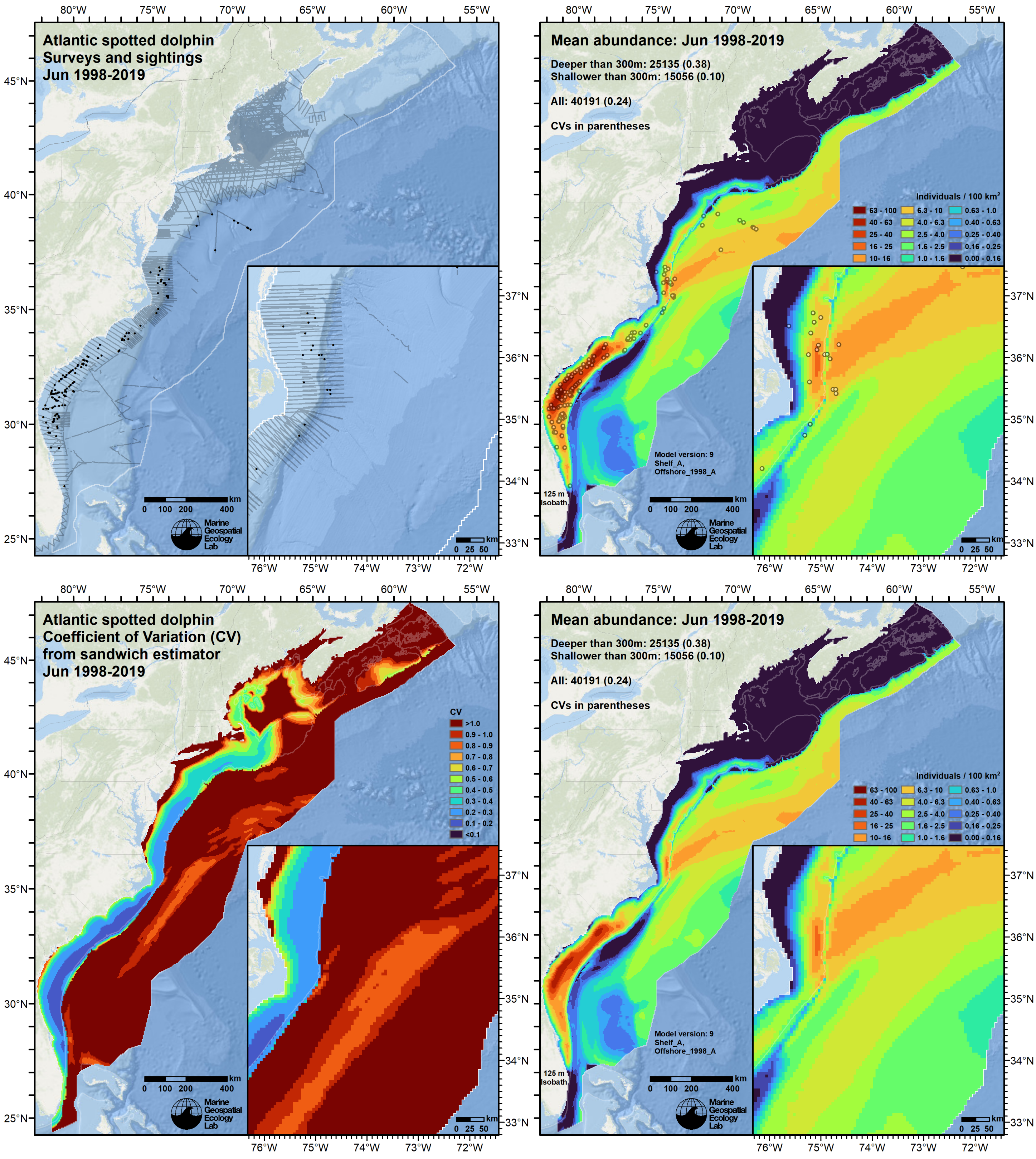


Figure 97: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of June for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

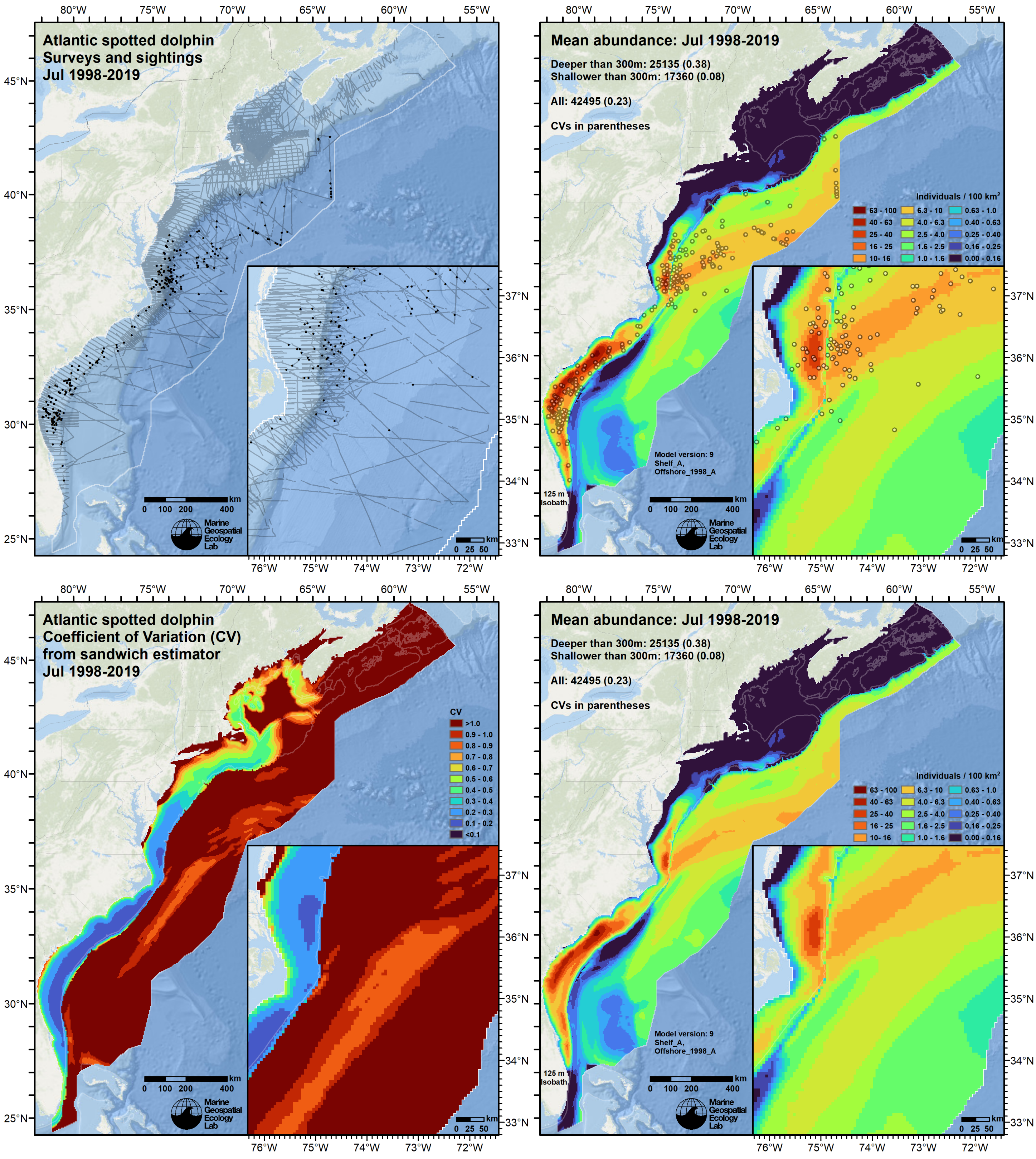


Figure 98: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of July for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

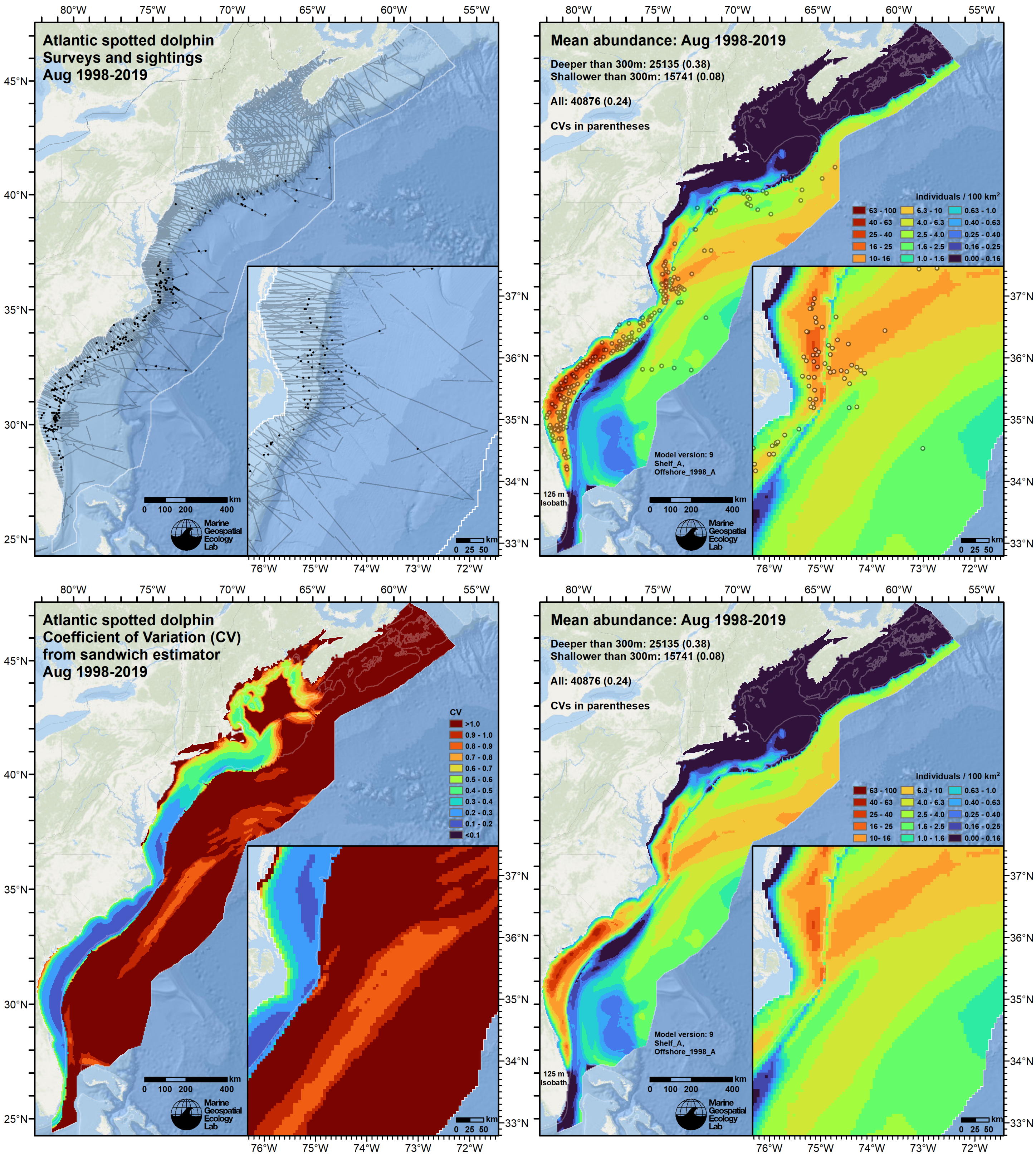


Figure 99: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of August for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

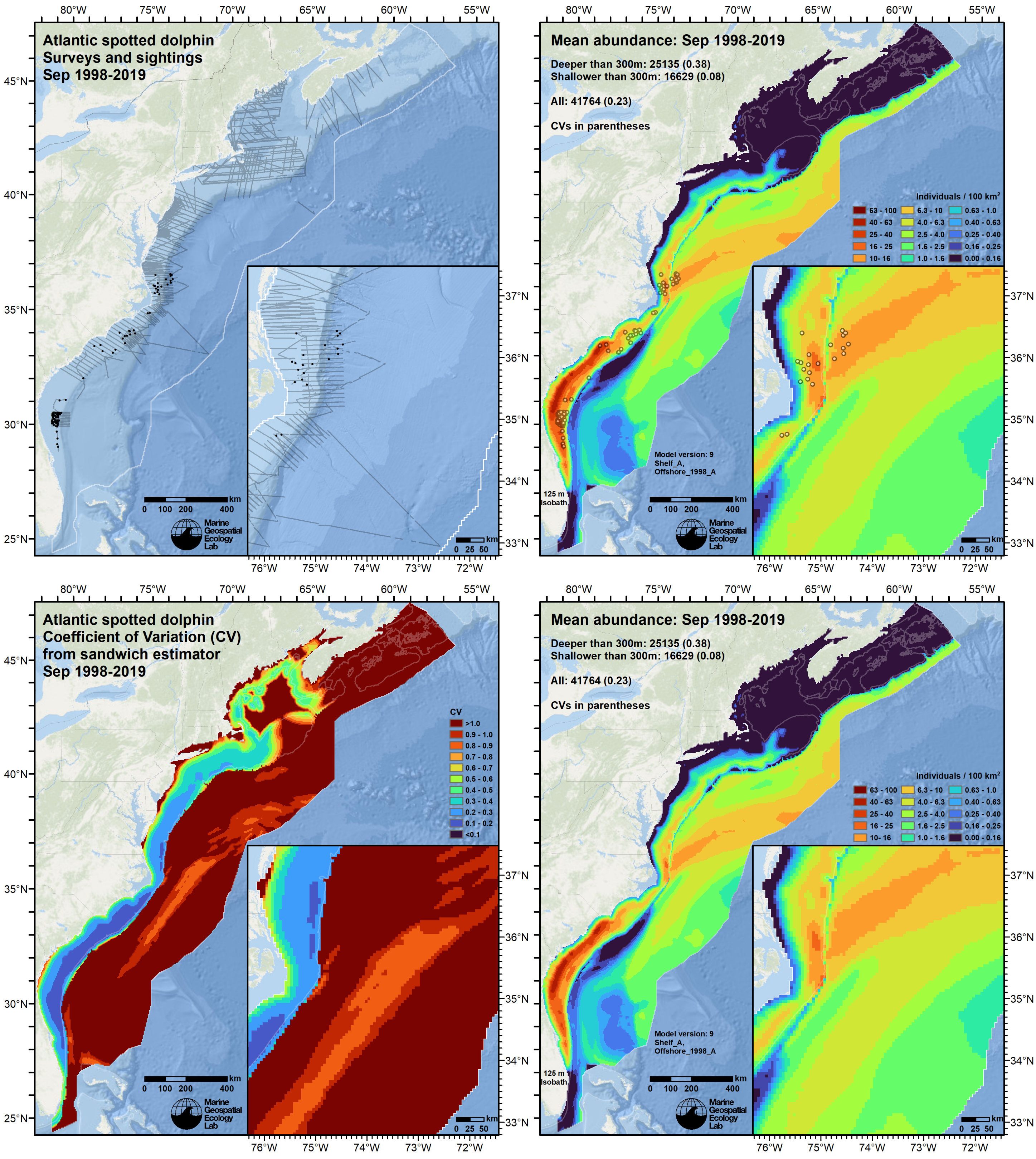


Figure 100: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of September for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

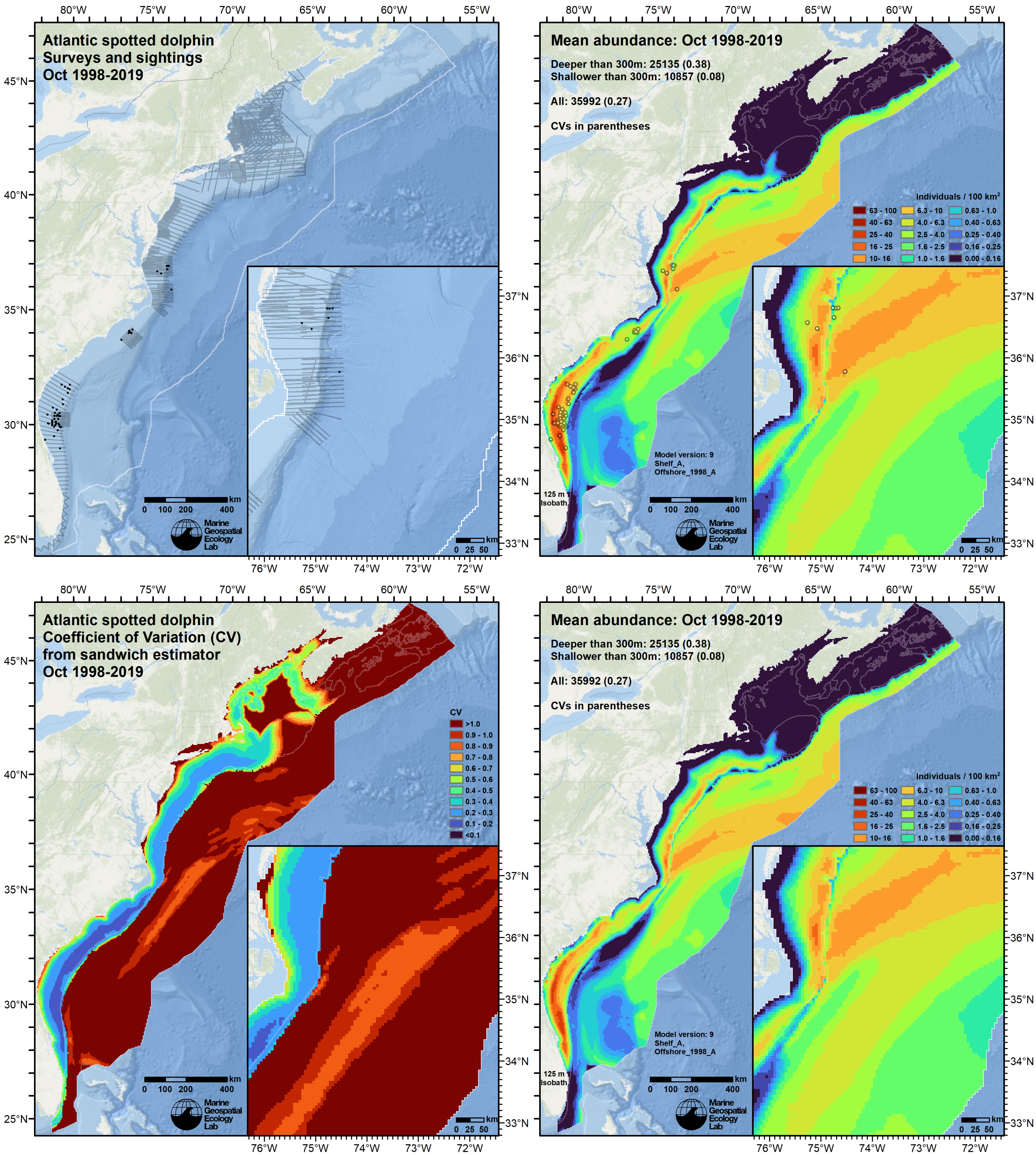


Figure 101: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of October for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

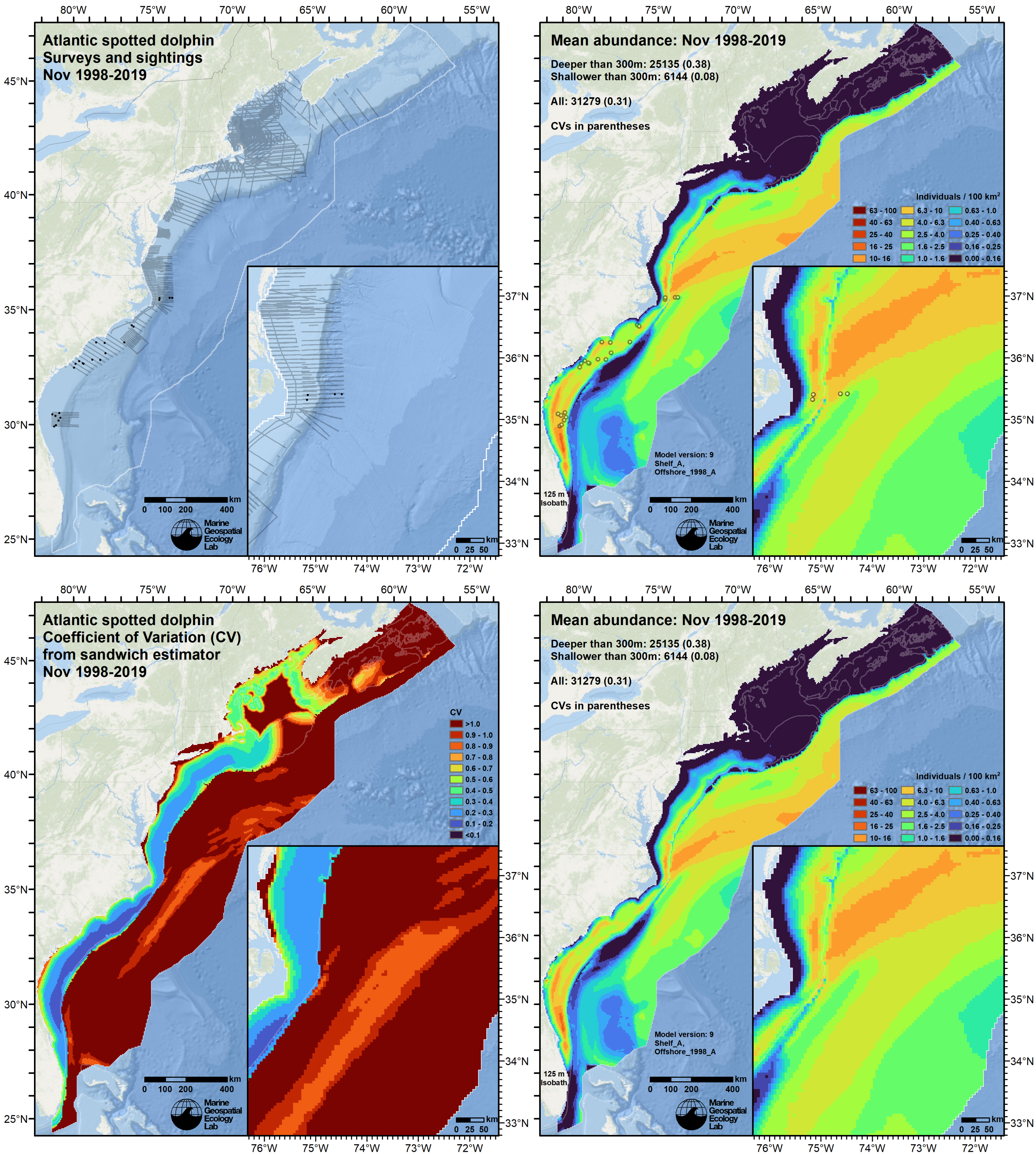


Figure 102: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of November for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

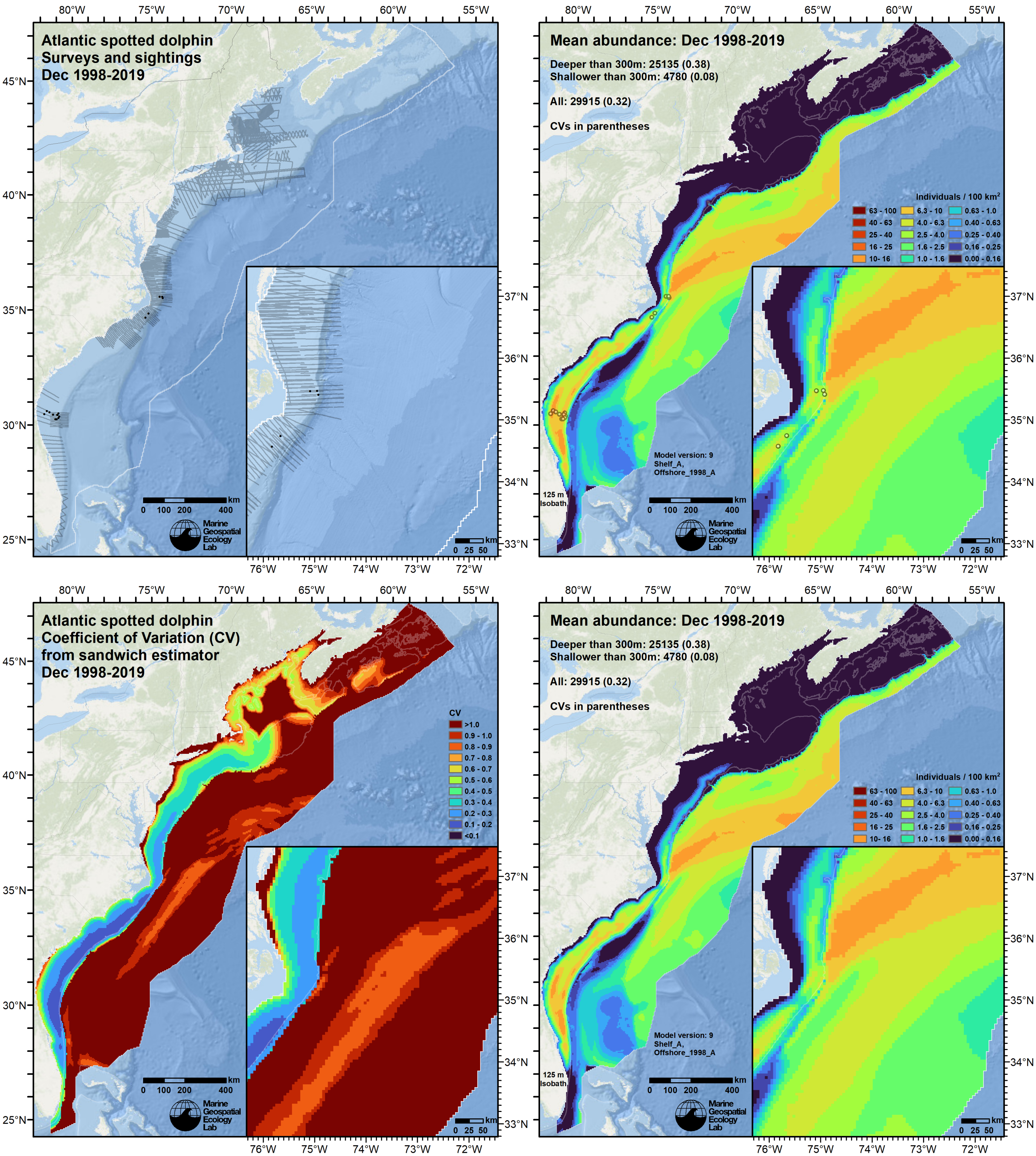


Figure 103: Survey effort and observations (top left), predicted density with observations (top right), predicted density without observations (bottom right), and coefficient of variation of predicted density (bottom left), for the month of December for the given era. Variance was estimated with the analytic approach given by Miller et al. (2022), Appendix S1, and accounts both for uncertainty in model parameter estimates and for temporal variability in dynamic covariates.

6.2 Abundance Comparisons

6.2.1 NOAA Stock Assessment Reports

Table 30: Comparison of regional abundance estimates from the 2019 NOAA Stock Assessment Report (SAR) ((ref:AChayes2020)) to estimates from this density model extracted from roughly comparable zones (Figure 104 below). The SAR estimates were based on a single year of surveying, while the model estimates were taken from the multi-year mean density surfaces we provide to model users (Section 6.1).

2021 Stock Assessment Report			Density Model		
Month/Year	Area	N_{est}	Period	Zone	Abundance
Jun-Aug 2016	New Jersey to Bay of Fundy[a]	8,247	Jun-Aug 1998-2019	NEFSC	13,930
Jun-Aug 2016	Central Florida to New Jersey[b]	31,674	Jun-Aug 1998-2019	SEFSC	25,632
			Jun-Aug 1998-2020	Canada[c]	1,245
Jun-Aug 2016	Total	39,921	Jun-Aug 1998-2019	Total	40,807

[a] Estimate originally from Palka (2020).
[b] Estimate originally from Garrison (2020).
[c] The SAR did not provide an estimate for this area. DFO's 2016 survey of the area did not report any sightings (Lawson and Gosselin (2018)).

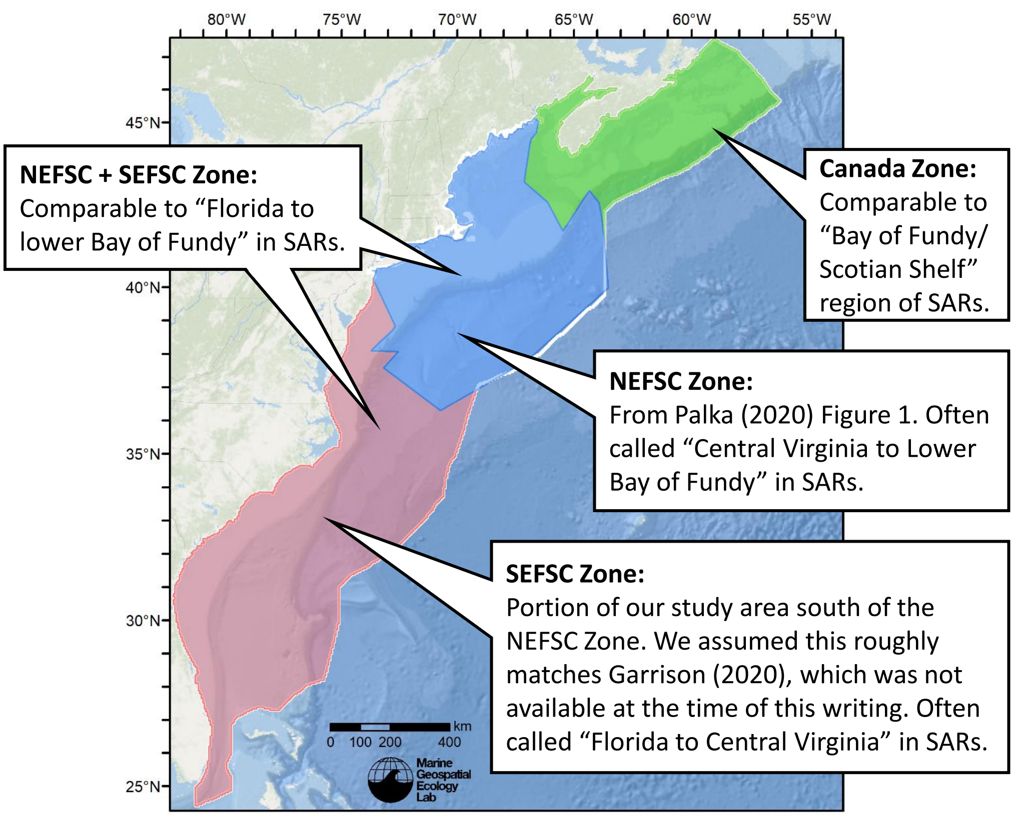


Figure 104: Zones for which we extracted abundance estimates from the density model for comparison to estimates from the NOAA Stock Assessment Report.

6.2.2 Previous Density Model

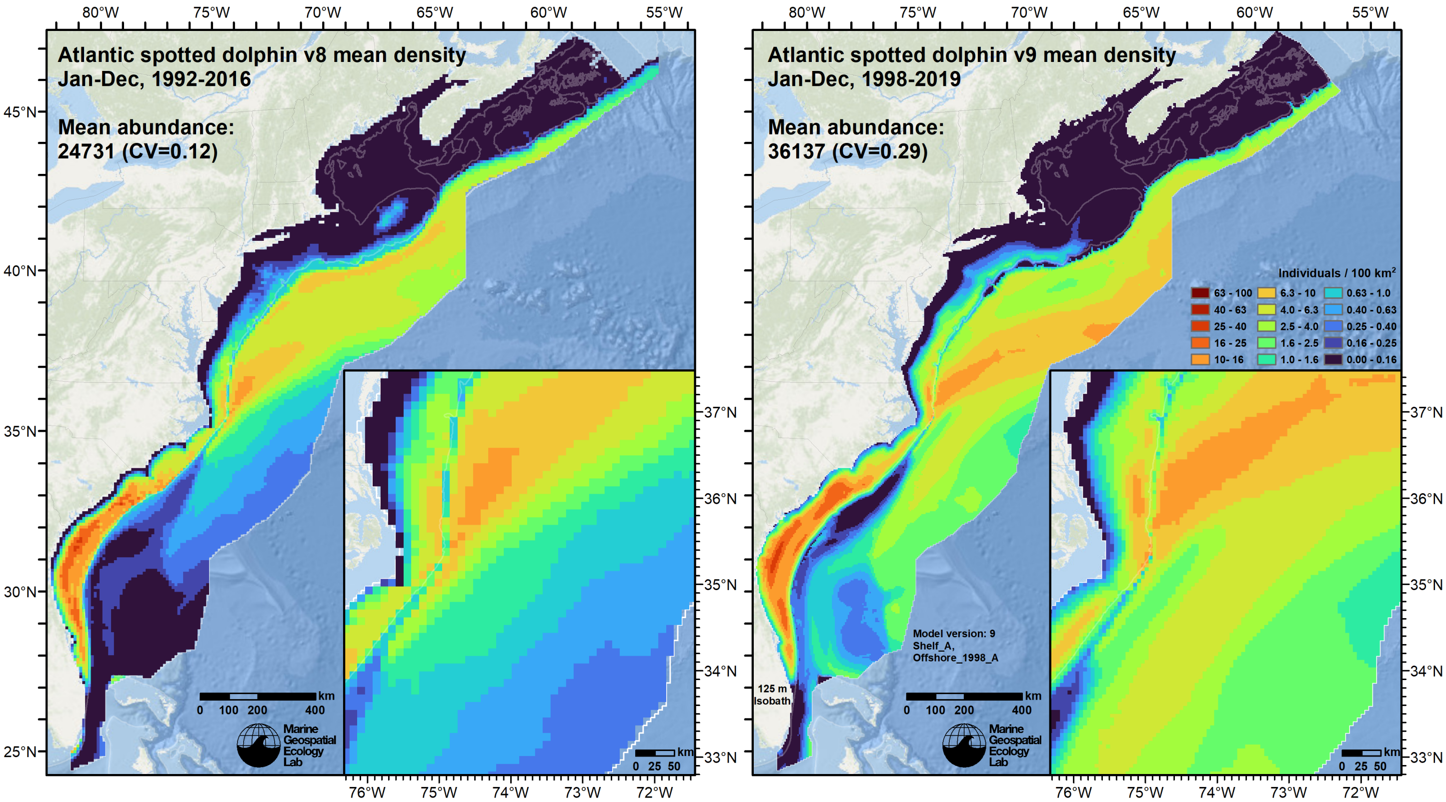


Figure 105: Comparison of the mean density predictions from the previous model (left) released by Roberts et al. (2018) to those from this model (right).

7 Discussion

This species presented an unusual case, with two ecotypes that showed relatively little spatial overlap, with one occupying the continental shelf, which had relatively strong survey coverage in all seasons, and the other occupying offshore waters, which had strong coverage only in summer. We initially considered summarizing predictions monthly for both regions/ecotypes, but several members of our collaboration with expertise in this species judged that non-summer coverage was too sparse for the offshore region/ecotype to offer monthly temporal precision there. Therefore, in a decision unique among all of the marine mammal models we built during this modeling cycle, we elected to summarize the shelf region monthly and the offshore region year-round.

In the shelf region, the model predicted highest densities in the mid-shelf (Figures 92-103), driven by the distance to shore covariate and several others (see Section 5.1). There was a distinct drop in most nearshore waters and approaching the continental shelf. The mid-shelf distribution is consistent with that reported by Griffin and Griffin (2003) for Atlantic spotted dolphins inhabiting the U.S. shelf of the eastern Gulf of Mexico.

The shelf region exhibited consistent moderate to high densities year-round south of Rodanthe, NC, the easternmost point in the state. North of here, high densities were predicted in June-November, and moderate to low densities in December-May. The prediction of non-zero density year-round north of Rodanthe was supported by the reporting of sightings in the vicinity of Rodanthe or north of it in all months except January, when effort was particularly low.

In the offshore region, the model predicted moderate densities across the deeper waters of the region with a peak north of Cape Hatteras where the Gulf Stream separates from the continental shelf. Higher densities extended into the Gulf Stream itself, and north of it, to the edge of the study area. In the south, low but non-zero densities were predicted across much of the Blake Plateau. Surveys in the modeled period (1998-2019) did not report any sightings there, but an earlier survey did report several sightings (Mullin and Ford 1992), and additional sightings from other sources can be seen in the OBIS-SEAMAP system (Halpin et al. 2009). Near-zero densities predicted in the extreme south, in the Florida Gap and Florida Straits, were supported by the findings of Herzing and Elliser (2016), who analyzed opportunistic sightings of cetaceans recorded on 17 years of vessel crossings between Palm Beach and Little Bahama Bank, with an average of 18 crossings per year, and reported that all Atlantic spotted dolphin sightings occurred near the Palm Beach Inlet.

Mean monthly abundance predicted by our model, totaled across both regions, ranged from a low of 29,915 in December to a high of 42,495 in July (Figure 91; Table 29). The mean summer (June-August) abundance (39,562), excluding our "Canada" zone, was about 1% lower than that (39,921) from the most recent NOAA Stock Assessment Report (Hayes et al. 2020). Regionally, our model predicted higher abundance for the "New Jersey to Bay of Fundy" area, and lower abundance for the "Central Florida to New Jersey" area (Table 30).

Compared to the previous model (version 8), this model (version 9) predicted 46% higher total abundance, with much of the addition coming in offshore waters. Offshore north of Cape Hatteras, density shifted south from the shelf break towards the Gulf Stream. South of Cape Hatteras, additional density was predicted far offshore, where additional surveys included in this model reported more sightings than the prior model. This strong change highlights the need to boost survey coverage offshore, particularly in non-summer seasons, in order to fully characterize species-habitat relationships of offshore taxa such as the oceanic ecotype of Atlantic spotted dolphin, and arrive at stable abundance estimates.

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