

Appendix 1. Stability selection

Methods

We applied stability selection (Meinshausen and Bühlmann 2010, Shah and Samworth 2013, see also Hofner et al. 2015 for details in the context of boosting) to identify base-learners, and thus covariates, that were commonly selected in the majority of randomly drawn subsamples of size $\lfloor n/2 \rfloor$ of the data. As proposed by Shah and Samworth (2013), we used $B = 50$ complementary pairs subsamples (i.e., we randomly split the data into two halves and used both to independently fit the model). This resulted in 100 total subsamples. We set the number of selected base-learners per boosting model (q) to 35 and established upper bounds of three and six for the occupancy and count model per-family error rates (PFER), respectively. These error bounds corresponded to an upper bound of $\alpha = 0.062$ for the per-comparison error rate in both models. The different thresholds reflect the different number of base-learners in the two models; occupancy models contained 48 base-learners while the count models contained twice as many base-learners (i.e., 48 each for the mean and overdispersion parameter). The choice of q is somewhat arbitrary; it is chosen to be large enough to incorporate all important variables in the model (Hofner et al. 2015). We used the unimodality assumption for the computation of the error bounds in the occupancy and count models (Shah and Samworth 2013, Hofner et al. 2015).

Results

Occupancy models

Given our specifications ($q = 35$; PFER upper-bound = 3, unimodality assumption), only base-learners selected in at least 99 of the 100 subsamples (i.e., $\pi_{\text{thr}} = 0.99$) were identified as stable (Figure 1.1).

Count models

Given our specifications ($q = 35$; PFER upper-bound = 6, unimodality assumption), only base-learners selected in at least 90 of the 100 subsamples (i.e., $\pi_{\text{thr}} = 0.9$) were identified as stable; this threshold applies to the simultaneous selection of base-learners for the conditional mean (μ) and conditional overdispersion (σ).

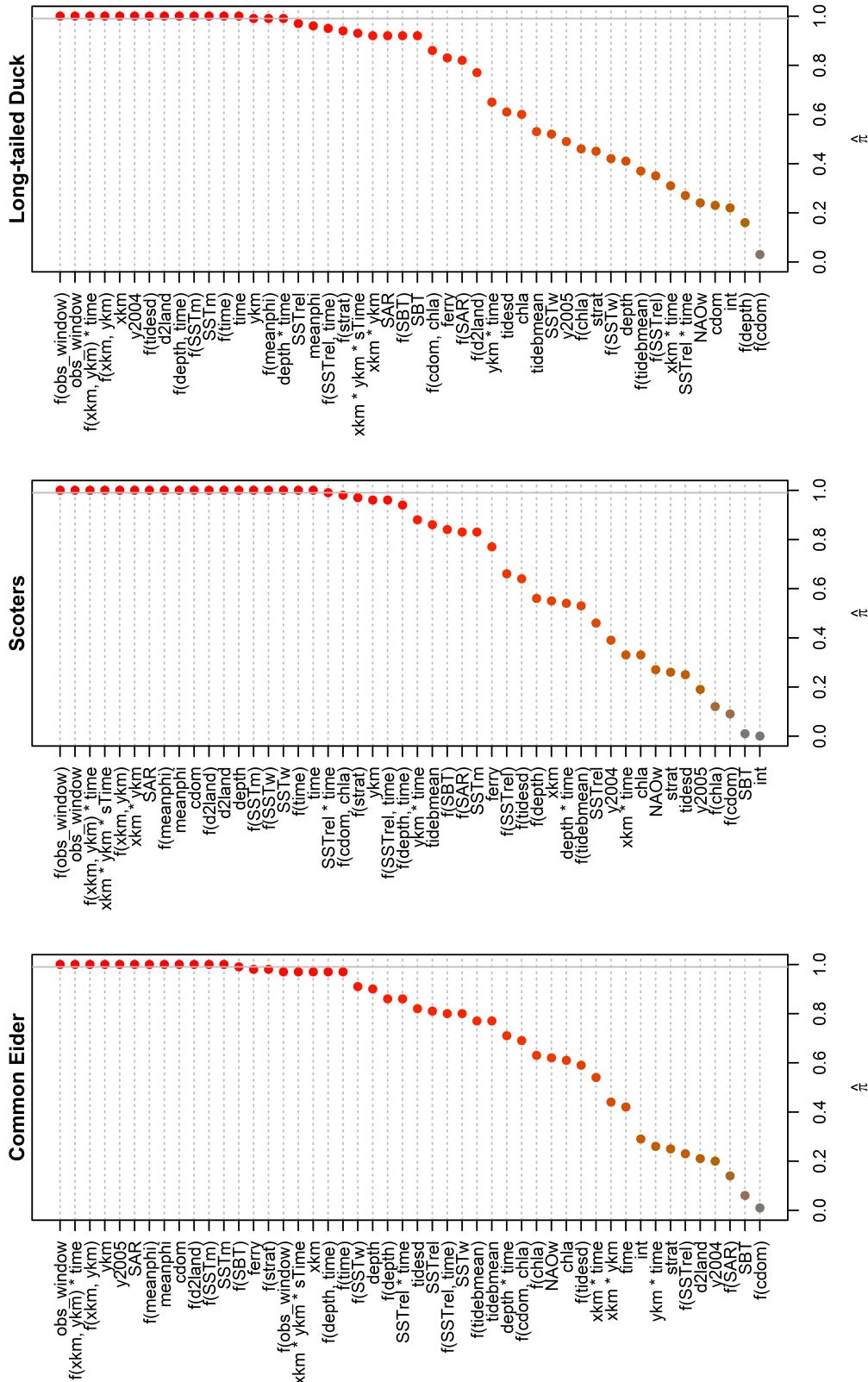


Figure 1.1 Stability selection using complementary pairs subsampling and unimodality assumption for sea duck occupancy models. The number of selected base-learners in each model run was set to $q = 35$. Base-learners with selection frequencies above the threshold (π_{thr} ; vertical gray line) were considered stable with upper bound PFER = 3.

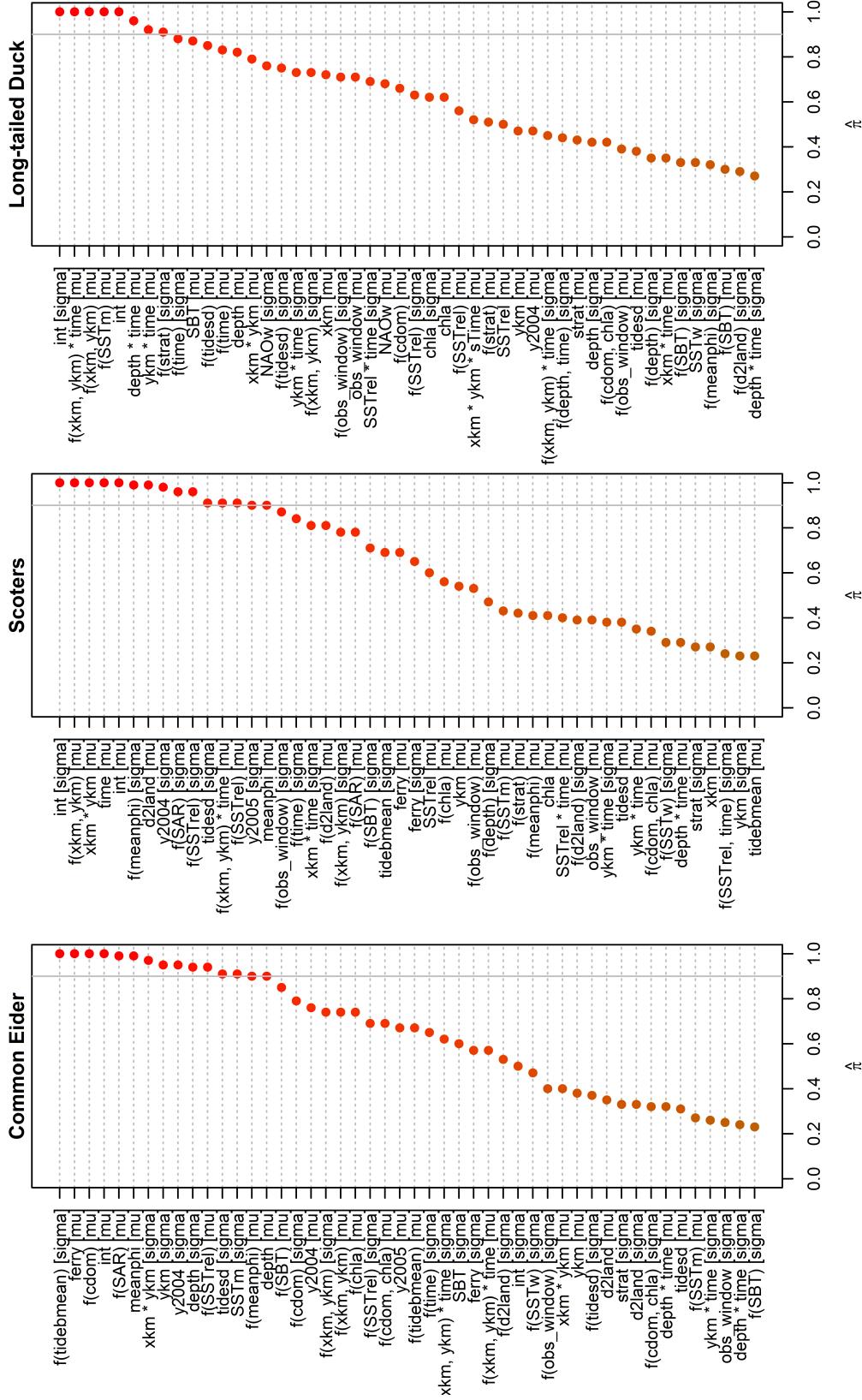


Figure 1.2 Stability selection using complementary pairs subsampling and unimodality assumption for sea duck conditional count models. The number of selected base-learners in each model run was set to $q = 35$. Base-learners with selection frequencies above the threshold (π_{thr} ; vertical gray line) were considered stable with upper bound PFER = 6. Only the top 48 (of 96 total) base-learners are illustrated. Brackets indicate the parameter (conditional mean, μ , or overdispersion, σ^2) to which the base-learner applies.

Appendix 2. Covariate details

We evaluated biophysical covariates (Table 2.1) expected to influence the distribution, abundance, and movements of sea ducks or, more likely, the distribution and availability of their benthic prey (e.g., mollusks and crustaceans); we did not have information related directly to the distribution of preferred prey. Biophysical covariates could be characterized as spatial (varying only among segments), temporal (varying within or among winters, but not among segments) or as spatiotemporal effects (varying among segments and within or among winters). We allowed the effect of bathymetry and relative sea surface temperature to vary over time within a given winter via interactions with day of season. We also included a survey effort covariate and covariates that were solely a function of segment geographic location, which we used to address potential spatial correlation in the data. We standardized (i.e., mean centered and scaled) all continuous covariates. Appendix 3 describes and illustrates the use of an R function to visualize the spatial and temporal distribution of these covariates in Nantucket Sound.

Table 2.1 Biophysical and survey covariates used to evaluate the distribution and abundance of Common Eider, Black, Surf, and White-winged Scoter, and Long-tailed Duck in Nantucket Sound during winters 2003 - 2005.

Variable (abbreviation)	Units	Type ¹	Variable	Description
Day of year (<i>time</i>)	day	T		seasonality; number of days from 31 December; negative values indicate days prior to 31 December
Bathymetry (<i>depth</i>)	m	S		bottom depth relative to mean high water; National Oceanic and Atmospheric Administration's (NOAA) National Geographic Data Center (NGDC): http://ngdc.noaa.gov/dem/squareCellGrid/download/385 (Eakins et al. 2009)
Sediment grain size (<i>meanphi</i>)	phi	S		sediment grain size (phi scale; Poti et al. 2012)
Sea floor surface area relative to planimetric area (<i>SAR</i>)	N/A	S		ratio of sea floor surface area (calculated from bathymetry; Jenness 2004) to planimetric area; estimate of the topographic variability of the sea floor
Epibenthic tidal velocity (mean; <i>tidebmean</i>)	m/s	S		average epibenthic tidal velocity during 2003-2005 based on monthly Finite-Volume Community Ocean Model (FVCOM) data (structured grids from http://fvcom.smast.umassd.edu/Data/FVCOM/NECOFS/Archive/ ; Chen et al. 2003, 2011)
Epibenthic tidal velocity (standard deviation; <i>tidesd</i>)	m/s	S		standard deviation of epibenthic tidal velocity during 2003-2005 base based on monthly FVCOM structured grids (Chen et al. 2003, 2011)

Variable (abbreviation)	Units	Variable type ¹	Description
Water column stratification potential (<i>strat</i>)	s^3/m^2	S	potential for seasonal thermal stratification of the water column (Simpson and Hunter 1974), calculated as the ratio of depth (h ; from bathymetry) to the third power of surface tidal velocity (u ; from monthly FVCOM structured grids; Chen et al. 2003, 2011); we report $\log_{10}(h/u^3)$ for each segment. Higher values indicate areas more prone to thermal stratification during the summer. Although the numerical value of $\log_{10}(h/u^3)$ at which stratification occurs depends on the choice of u , relative values among locations remain consistent (Simpson and Sharples 2012)
Chlorophyll-a (<i>chl</i> a)	mg/m^3	S	geometric mean of monthly composite chlorophyll-a levels from July 2002 (first available) to March 2006; data from the Aqua MODIS satellite via NOAA Environmental Research Division's Data Access Program (ERDDAP): http://coastwatch.pfeg.noaa.gov/erddap/info/ercdMEchloraday/index.html
Chromophoric dissolved organic material (<i>cdom</i>)	N/A	S	geometric mean of monthly composite chromophoric dissolved organic material levels (measured based on absorbance values) from July 2002 (first available) to March 2006; data from the Aqua MODIS satellite via NOAA ERDDAP: http://coastwatch.pfeg.noaa.gov/erddap/info/ercdMEcdomday/index.html . No units (absorbancy measure). Note the experimental nature of this product.

Variable (abbreviation)	Units	Variable type ¹	Description
Sea bottom temperature (SBT)	°C	ST	sea bottom (epibenthic) temperature averaged from May to October for each year (2003-2005) from monthly FVCOM structured grids (Chen et al. 2003, 2011). May through October corresponds to the period of settling of relevant bivalve spawn in the area (Evans et al. 2011), and temperature potentially influences mussel settling and growth (Fay et al. 1983, Newell 1989)
Sea surface temperature (monthly; SST_m)	°C	ST	monthly sea surface temperature from monthly FVCOM structured grid (Chen et al. 2003, 2011); available alternative sea surface temperature sources possessed too coarse resolution (e.g., AHVRR Pathfinder; Zipkin et al. 2010) or inconsistent measurements in the study area (e.g., Aqua MODIS; Winiarski et al. 2013)
Sea surface temperature (Nov - Mar; SST_w)	°C	ST	average winter (November through March) sea surface temperature from monthly FVCOM structured grids (Chen et al. 2003, 2011)
Sea surface temperature (relative; SST_{rel})	°C	ST	difference between the monthly sea surface temperature of a segment and the average sea surface temperature of the entire study area; based on monthly FVCOM structured grids (Chen et al. 2003, 2011)

Variable (abbreviation)	Units	Variable type ¹	Description
North Atlantic Oscillation (Dec - Mar; NAO_w)	N/A	T	winter (December through March) North Atlantic Oscillation index based on the principal component time series of the leading empirical orthogonal function of sea level pressure anomalies over the Atlantic sector (Hurrell 1995, Hurrell and Deser 2010); data from the Climate Analysis Section, National Center for Atmospheric Research: https://climatedataguide.ucar.edu/climate-data/hurrell-north-atlantic-oscillation-nao-index-pc-based (accessed 14 April 2014)
Distance to land (d_{land})	km	S	distance to the nearest location of zero depth (from bathymetry)
∞	Ferry route within 1 km (<i>ferry</i>)	N/A	S indicator of whether the ferry route from Cape Cod to Nantucket (Massachusetts Department of Transportation, Office of Transportation Planning) intersects a given segment; the ferry route was buffered by 1 km to accommodate potential sea duck responses to ship traffic at a distance and uncertainty in ferry route (Larsen and Laubek 2005, De La Cruz et al. 2014). Ferries traversed this route approximately 16 times per day during the study period
Winter 2004 (<i>y2004</i>)	N/A	T	indicator comparing surveys occurring from November 2004 through April 2005 with those occurring from December 2003 through April 2004
Winter 2005 (<i>y2005</i>)	N/A	T	indicator comparing surveys occurring from October 2005 through March 2006 with those occurring from December 2003 through April 2004

Variable (abbreviation)	Units	Variable type ¹	Description
Easting (xkm)	km	S	distance between the easting of a segment center from the median easting of all segments surveyed in the study area; negative and positive values indicate segments west and east of the median easting, respectively
Northing (ykm)	km	S	distance between the northing of a segment center from the median northing of all segments surveyed in the study area; negative and positive values indicate segments south and north of the median northing, respectively
Survey effort (obs_window)	km^2	ST	area of strip transect surveyed in a given segment on a given survey date; calculated as the product of the length and width of the strip transect

¹ Variable type: S (spatial; varying only among segments); T (temporal; varying only over time); ST (spatiotemporal; varying in space and time)

Appendix 3. Visualizing covariate distribution

We illustrate the visualization of biophysical covariates used in the construction of sea duck distribution and abundance models in Nantucket Sound. A custom function (`plot_covariate`) plots, as applicable, the spatial distribution and temporal dynamics of these covariates in the study area.

The arguments of the `plot_covariate` function allow some flexibility in manipulating the plotted output:

```
## function (z = "depth", data = env.segs, x = "x", y = "y", plotwind = FALSE,
##           segs = TRUE, agg.seg = c(NA, "mean", "sum"), winter = "winter",
##           month = "date", legend.title = NULL, legend.size = 10, scale = FALSE,
##           diverge = FALSE)
## NULL
```

Only a few arguments are likely to be modified in the current context: `z` defines the covariate of interest, and can take any of the following values (see Appendix 2 for definitions): SSTw, SSTm, SSTrel, SBT, chla, cdom, meanphi, depth, d2land, SAR, tidebmean, tidesd, strat, NAOw, ferry, or length. `plotwind` and `segs` are logicals indicating whether the user would like to plot the permitted wind energy development area or segment boundaries (see Figure 1 in manuscript), respectively. `agg.seg` allows temporally dynamic (i.e., varying within a winter or among winters) covariate values to be summarized (e.g., average, sum) within each segment; the default is to plot their dynamics, and not summarize, within the study area. `legend.title` and `legend.size` permit the modification of the legend title and legend size, respectively. The `scale` option standardizes `z` prior to plotting, and the `diverge` option changes the legend of a continuous covariate to divergent colors on either side of zero, a useful modification for visualizing standardized covariates.

Spatial covariates

The bathymetry of Nantucket Sound varied only in space, and can be visualized with the default options (Figure 3.1, left panel). More informatively, perhaps, the standardized depth values can be plotted with a legend scale diverging around zero, as well as a custom legend title and the wind development area indicating (Figure 3.1, right panel), using:

```
plot_covariate("depth") # Figure 3.1, left
# Figure 3.1, right
plot_covariate("depth", legend.title = "Scaled\ndepth (m)",
               plotwind = TRUE, scale = TRUE, diverge = TRUE)
```

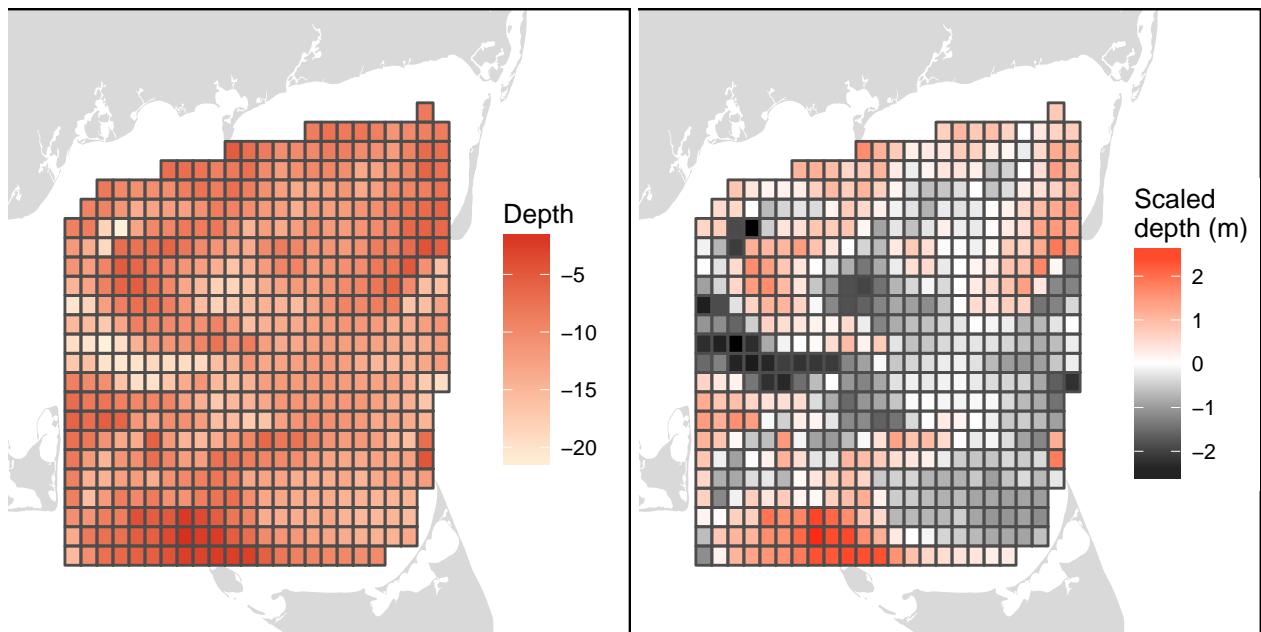


Figure 3.1. Nantucket Sound bathymetry (left) and standardized with a diverging legend scale, custom legend title, and delineated wind development area (right).

Spatiotemporal covariates

Certain covariates varied spatially within Nantucket Sound but also monthly and/or annually; `plot_covariate` identifies these temporal changes and divides the plot accordingly. For example, the average sea surface temperature from November through March (SST_w) varied among segments in Nantucket Sound, as well as on an annual basis (Figure 3.2). Sea surface temperature relative to other segments in a given month (SST_{rel}) varied spatially, annually, and monthly (Figure 3.3).

```
plot_covariate("SSSTw", scale = TRUE, diverge = TRUE) # Figure 3.2
```

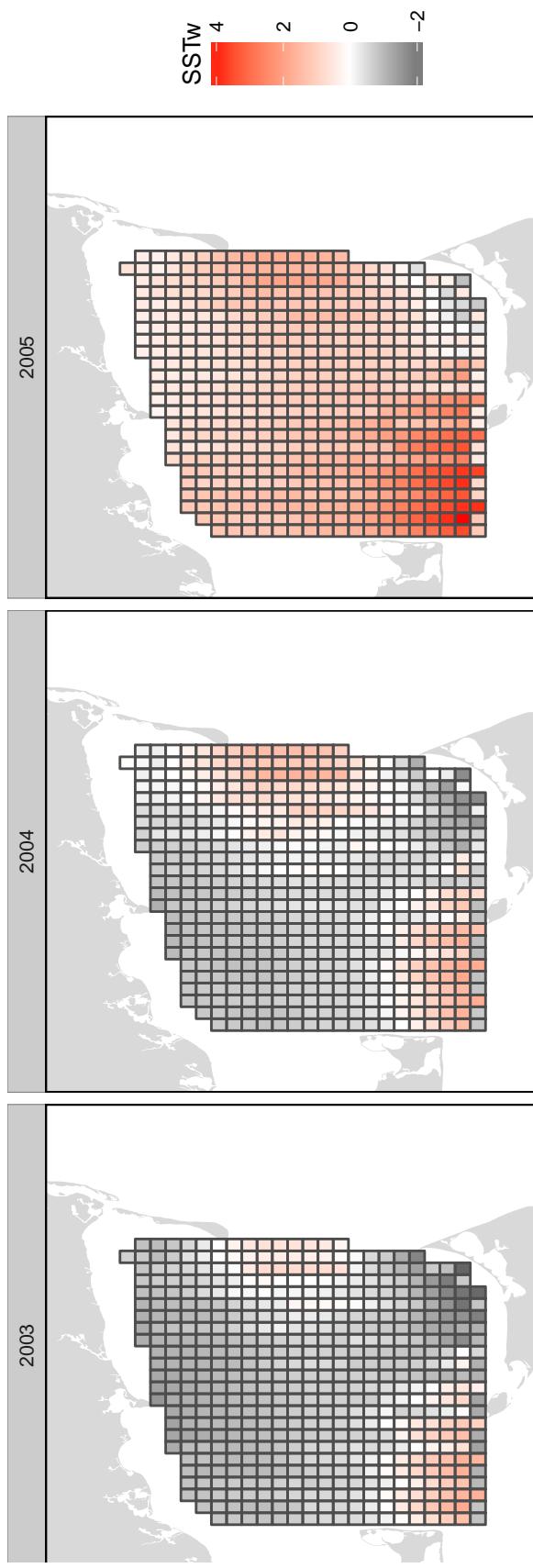


Figure 3.2. Spatial and annual variation in standardized sea surface temperature from November through March (SSSTw) in Nantucket Sound.

```
plot_covariate("SSSTrel", segs = FALSE, scale = TRUE, diverge = TRUE) # Figure 3.3
```

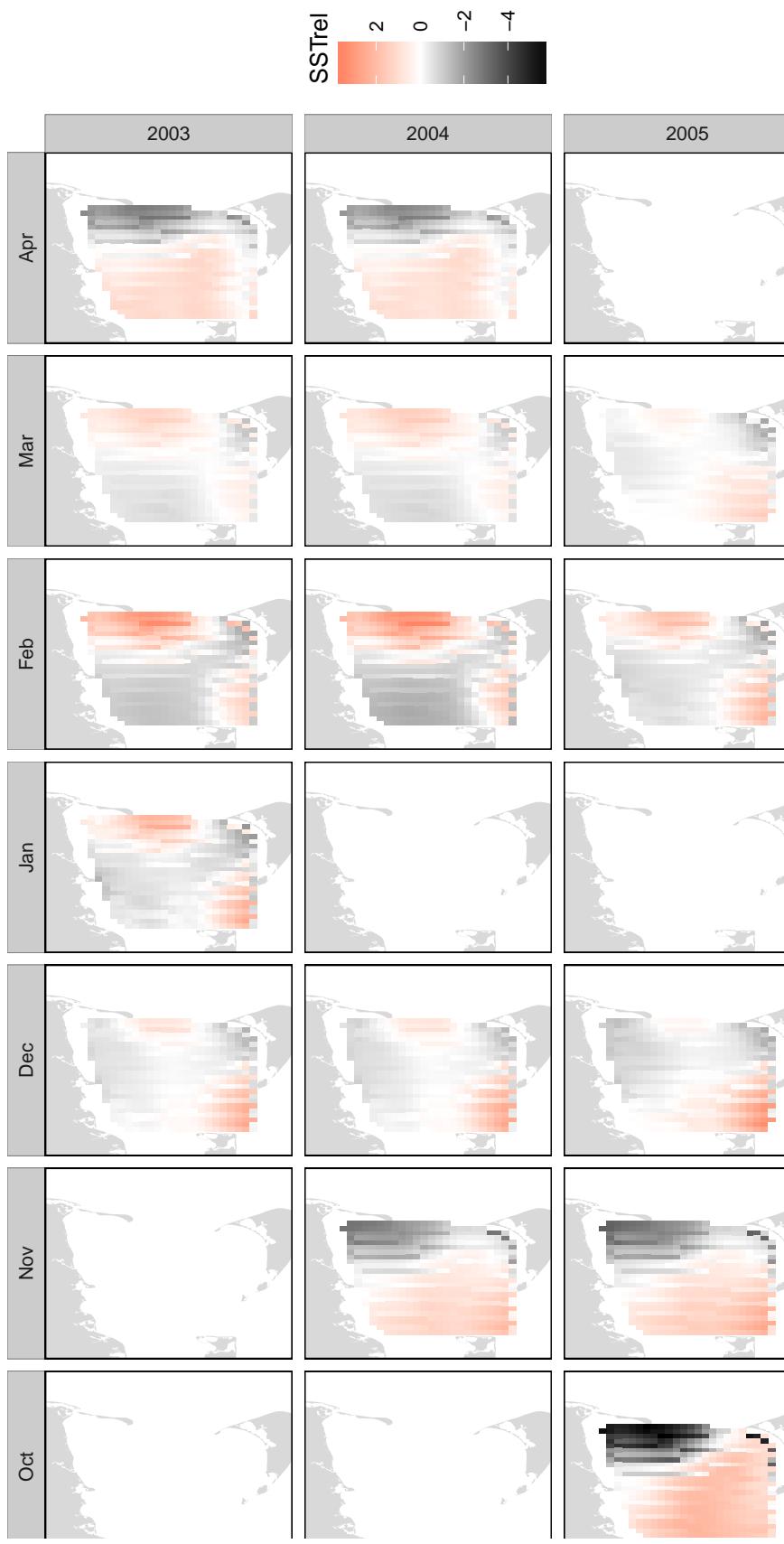


Figure 3.3. Spatial, monthly, and annual variation in standardized sea surface temperature relative to other segments (SSSTrel) in Nantucket Sound. I get a warning that “Non Lab interpolation is deprecated”. Furthermore, I have plenty of empty panels. Is that correct? If so, state this and explain why this happens.

Lastly, it can be useful to aggregate temporally-dynamic covariate values within segments. For example, the total length of transect surveyed in each segment over the course of this study is obtained with:

```
plot_covariate("length", agg.seg = "sum",
               legend.title = "Survey effort\n(km transect)") # Figure 3.4
```

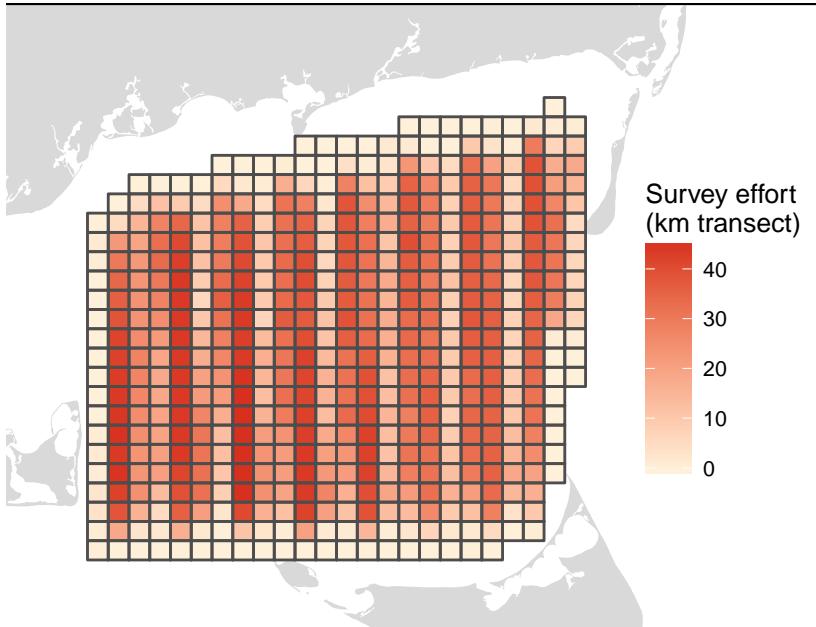


Figure 3.4. Total length (km) of strip transects surveyed in 504 2.25km² segments during 30 aerial sea duck surveys in Nantucket Sound.

Appendix 4. Early stopping

Occupancy models

All occupancy models converged to the maximum likelihood estimates (i.e., did not stop early; Figure 4.1). Failure to stop early sometimes happens in data sets with many observations and strong effects (see comment of Kneib in Bühlmann et al. 2014). This suggests that the effects of the environmental variables on sea duck occupancy are rather complex.

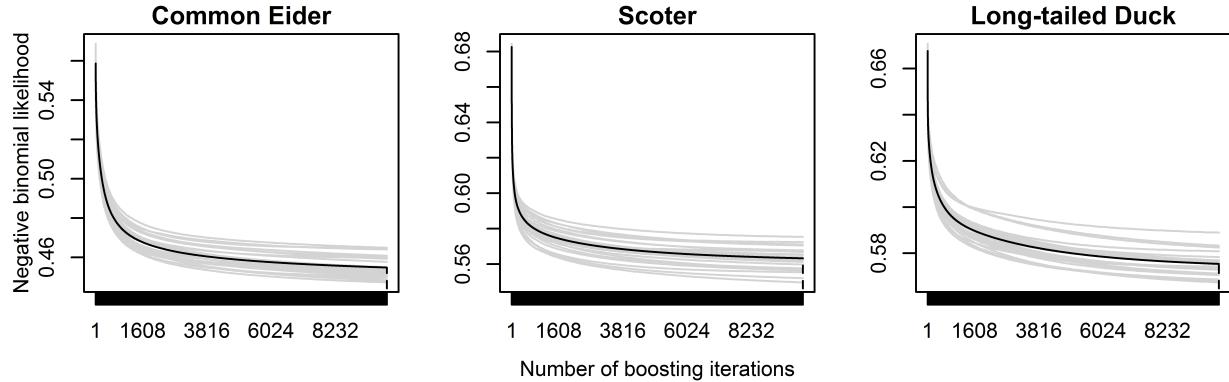


Figure 4.1 Bootstrapped out-of-bag empirical risk in sea duck occupancy models based on 25-fold subsampling. Gray lines indicate the out-of-bag risk on each subsample and the black line indicates the average out-of-bag risk; the optimal iteration is indicated by the dashed vertical line.

Count models

In contrast to occupancy model, bootstrapping prescribed early stopping for both parameters in all count models (Figure 4.2).

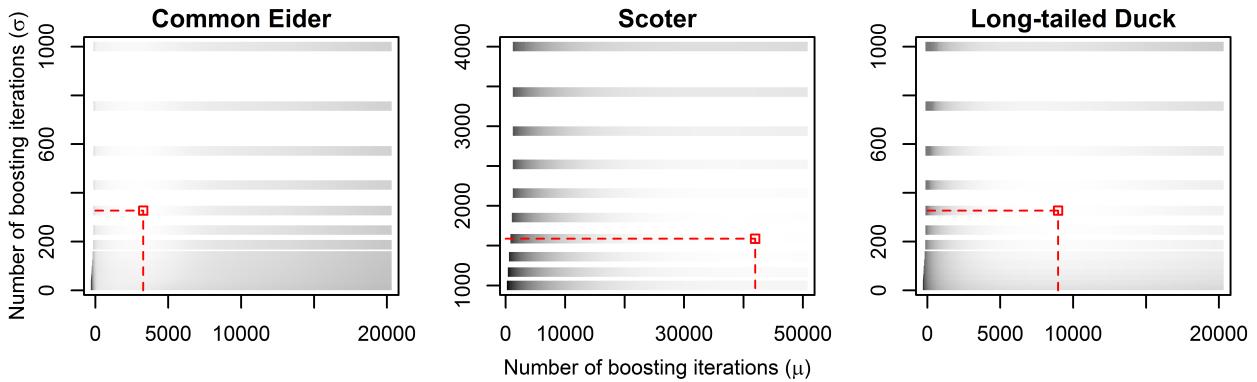
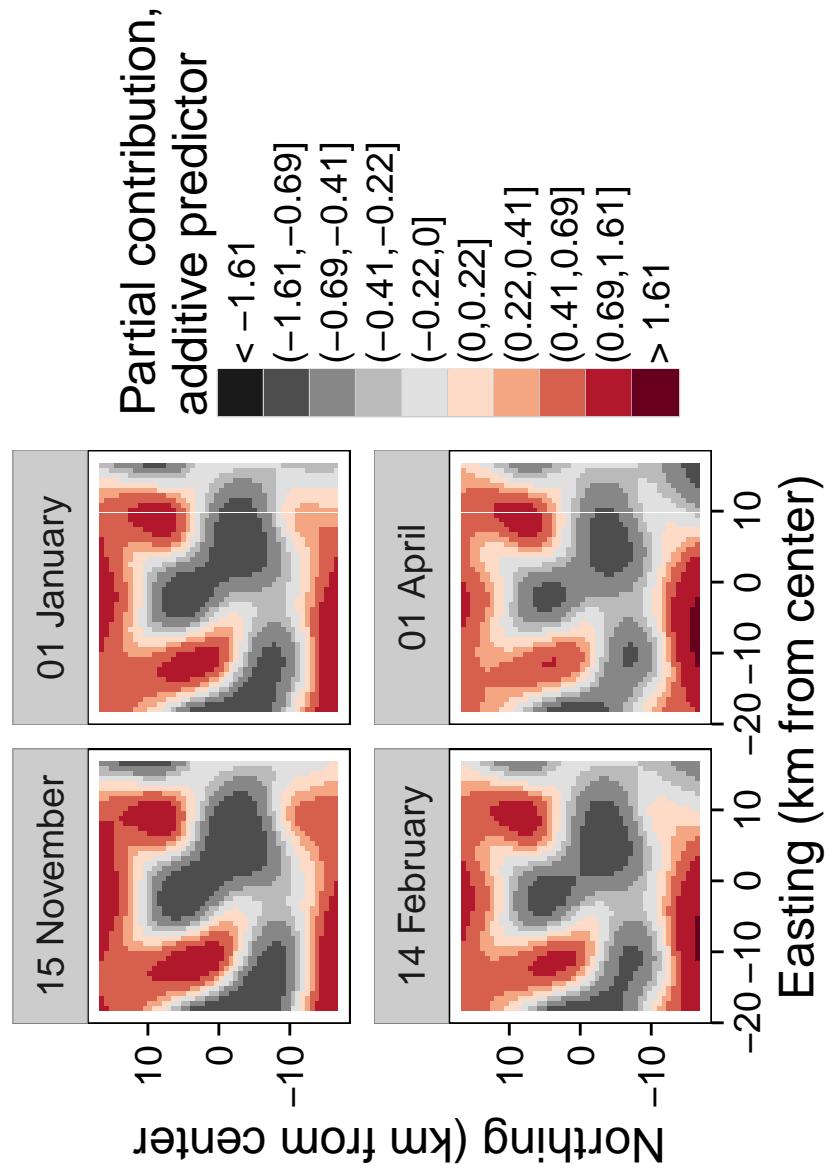


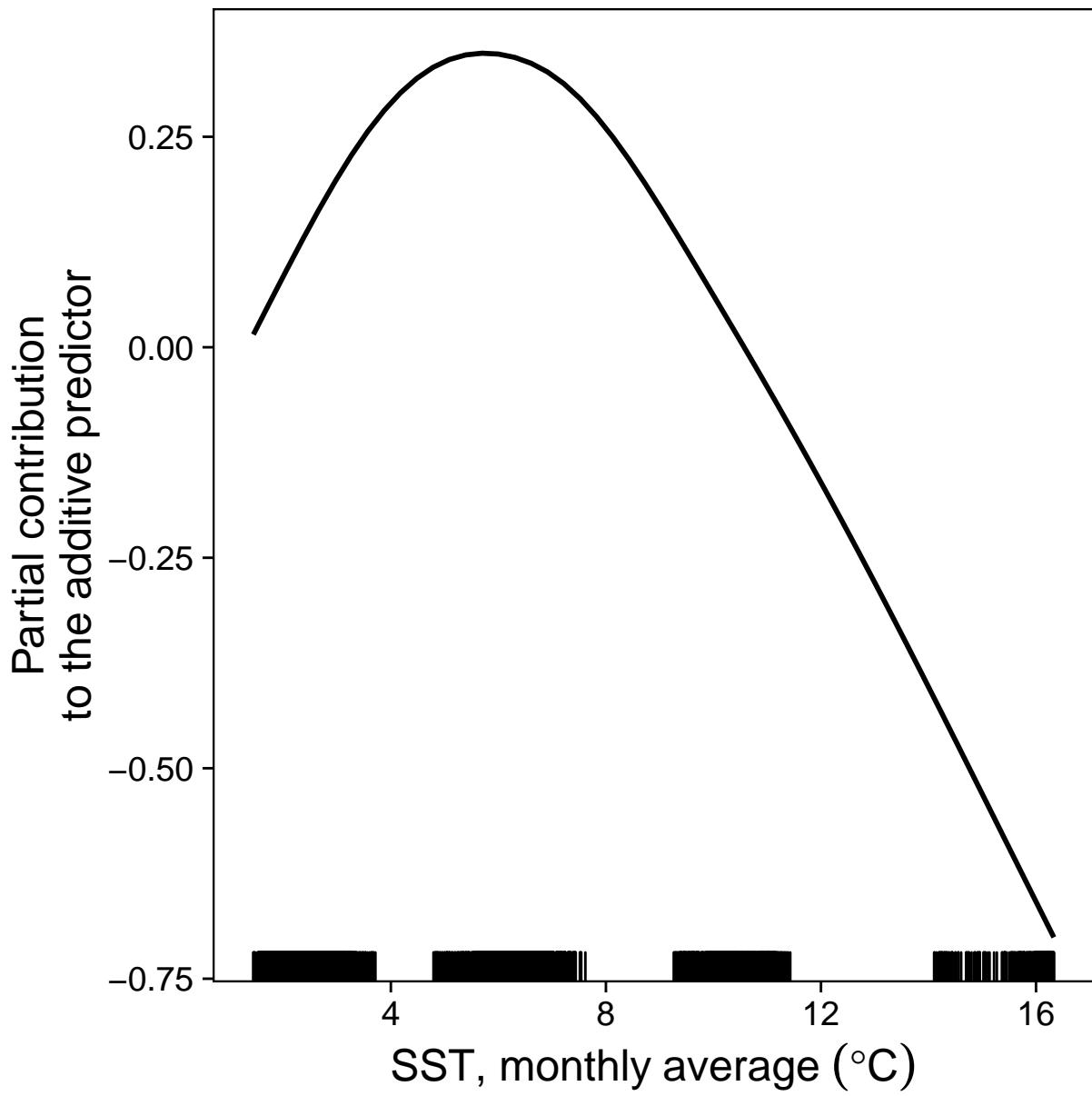
Figure 4.2 Bootstrapped out-of-bag empirical risk in sea duck conditional count models based on 25-fold subsampling. Lighter colors indicate lower average out-of-bag risk (over the 25 samples) for a given combination of m_{stop} -values for μ and σ ; the optimal combination is indicated by the red square.

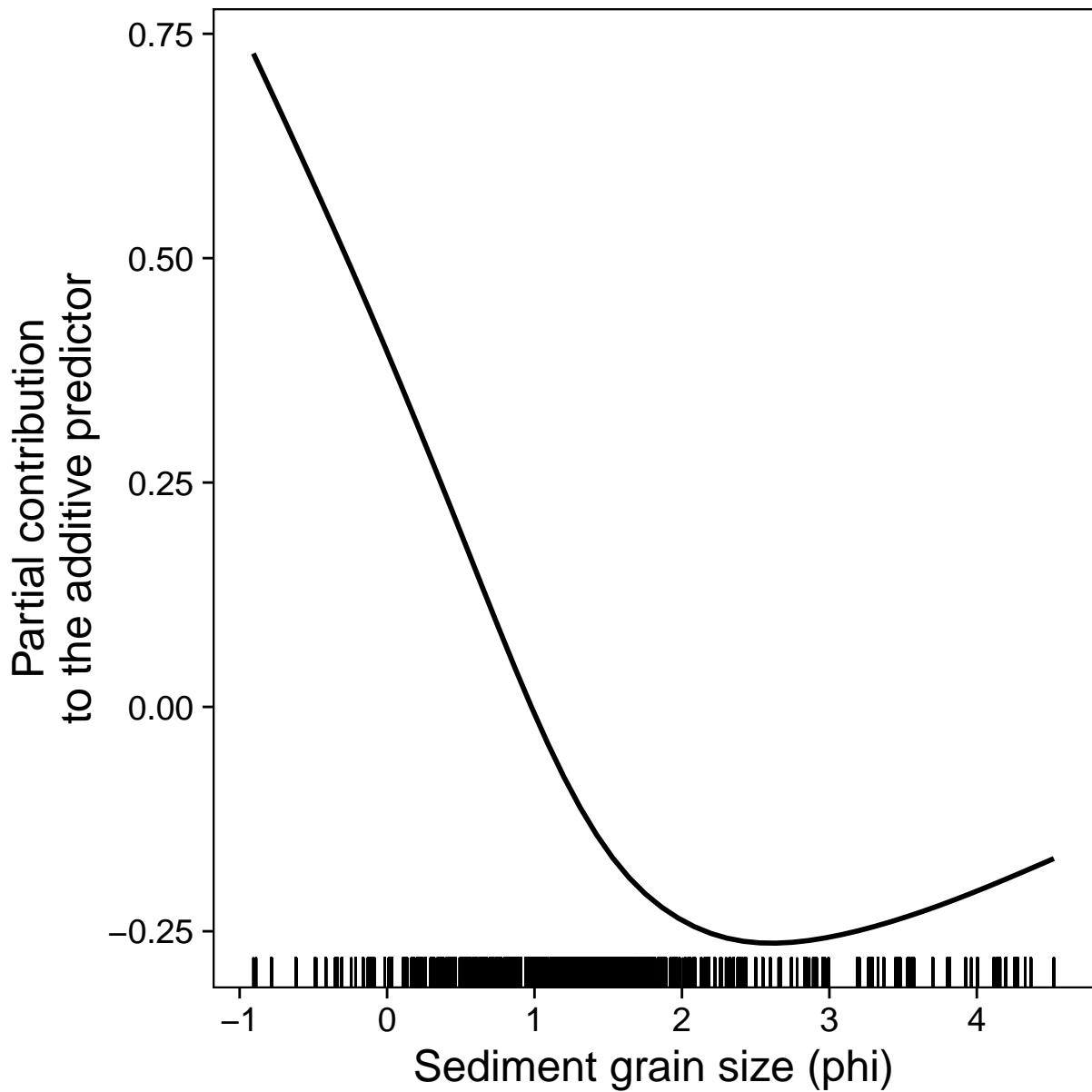
Appendix 5. Common Eider stable covariate effects

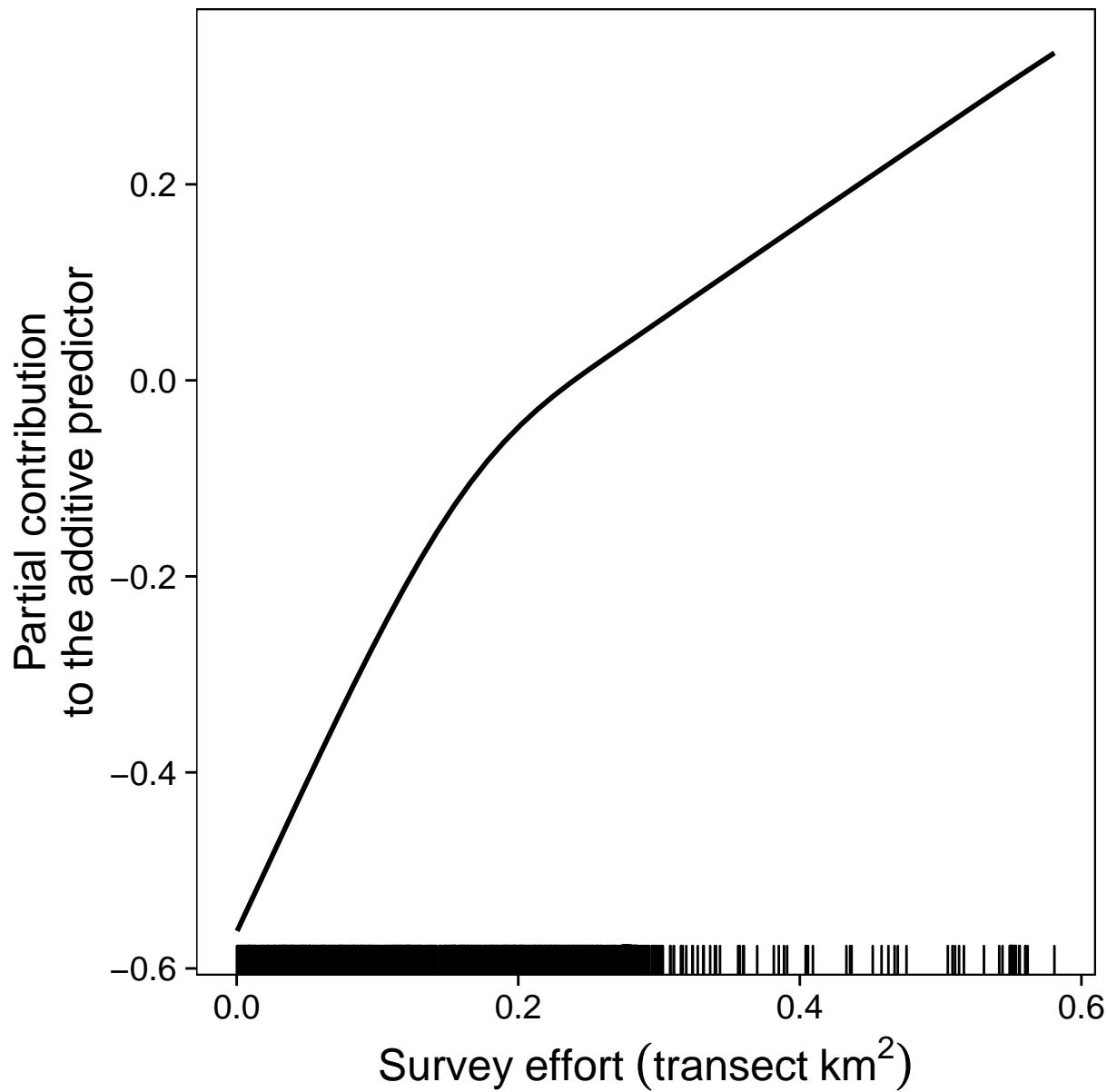
Marginal functional plots of the relationships between covariates (controlling for all other variables; i.e., at their mean values) and the occupancy, conditional mean abundance, and conditional overdispersion of abundance of Common Eider in Nantucket Sound, Massachusetts, USA. Covariate plots are ordered roughly in descending order of the magnitude of their influence on the additive predictor in each model (or model parameter for count models). Vertical lines along the x -axis (i.e., rug plots) indicate observed covariate values. Covariates (and any abbreviations) are defined in detail in Appendix 2; only effects selected to be stable (see Appendix 1) are depicted.

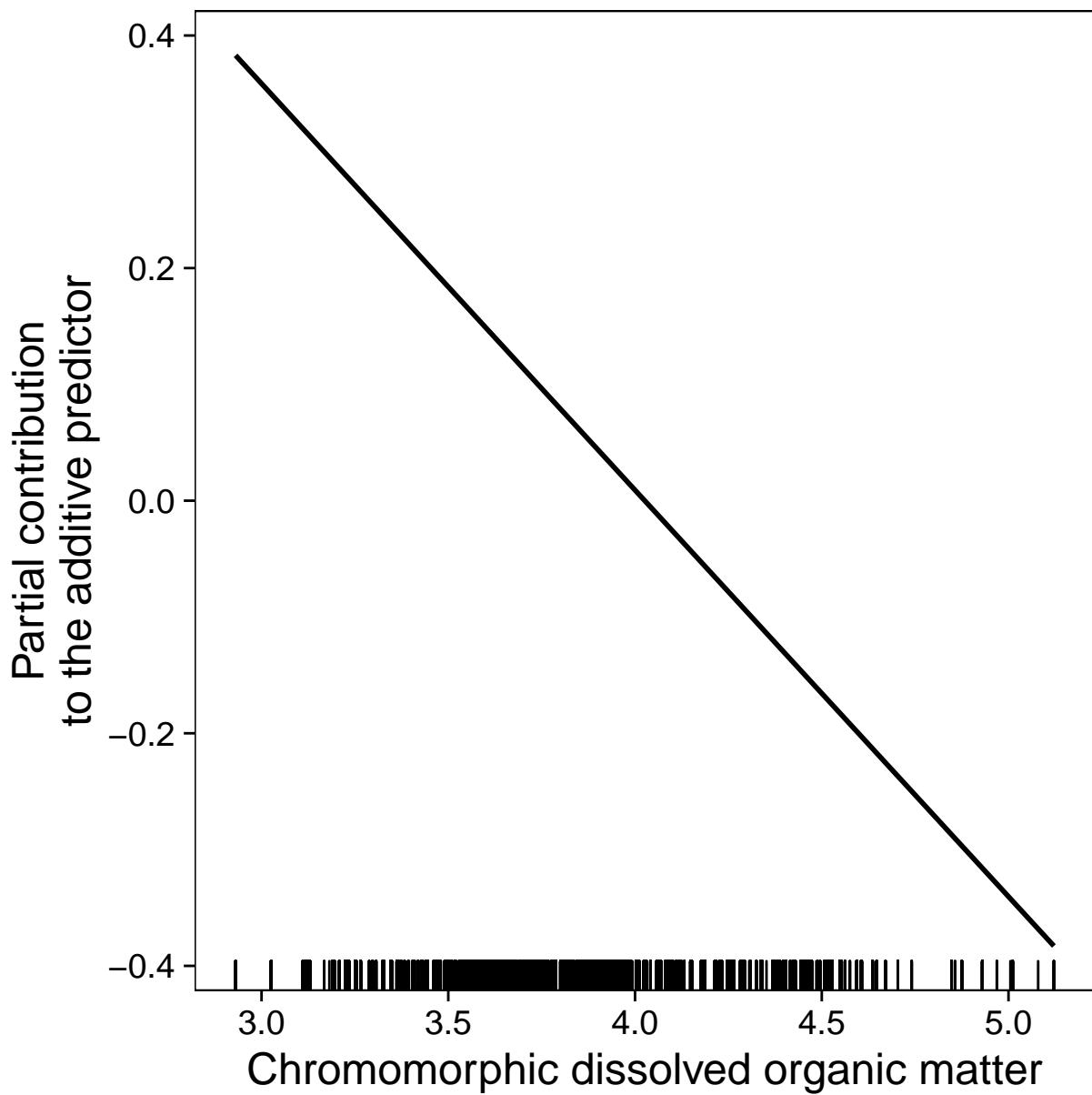
Occupancy

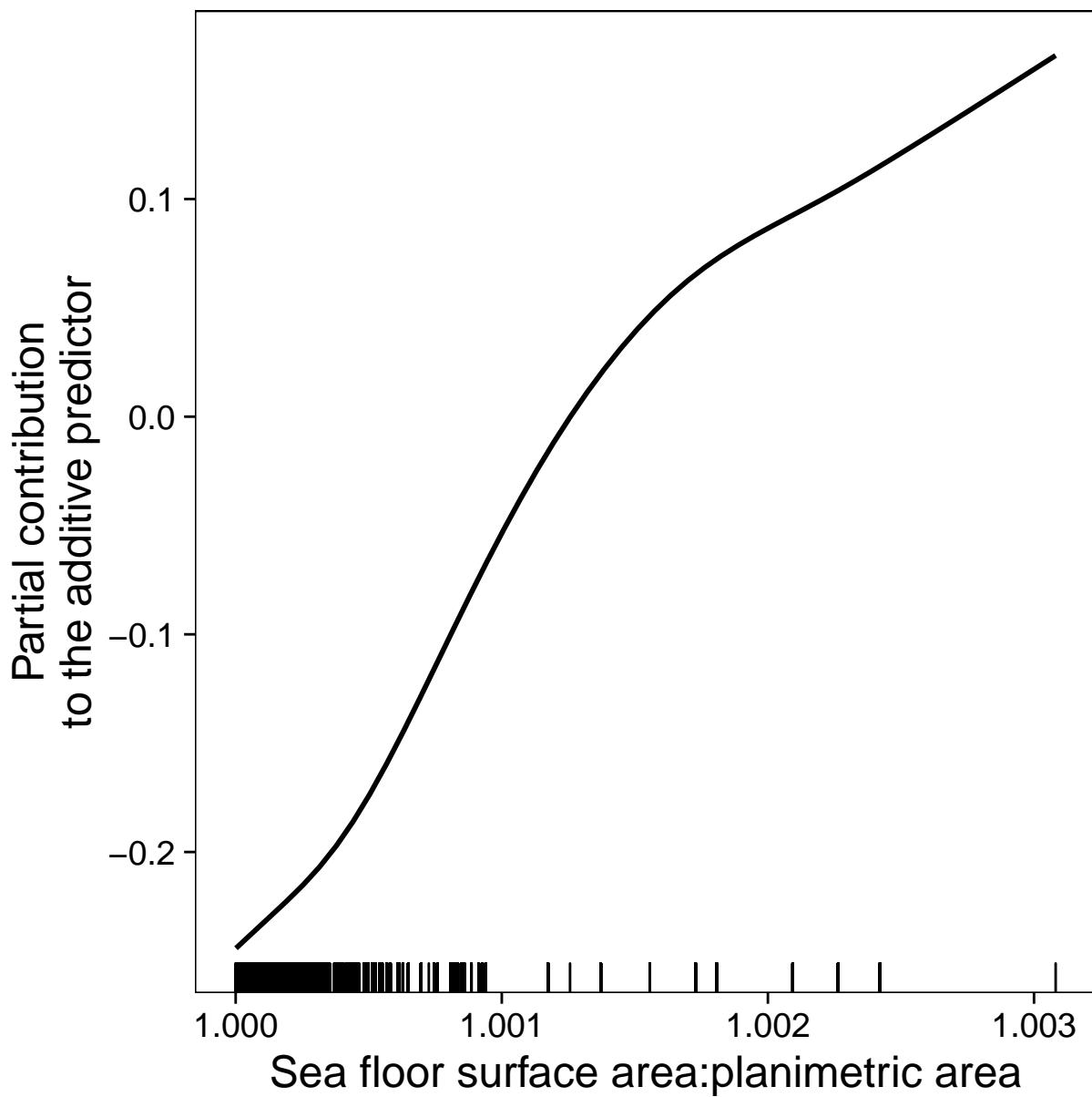


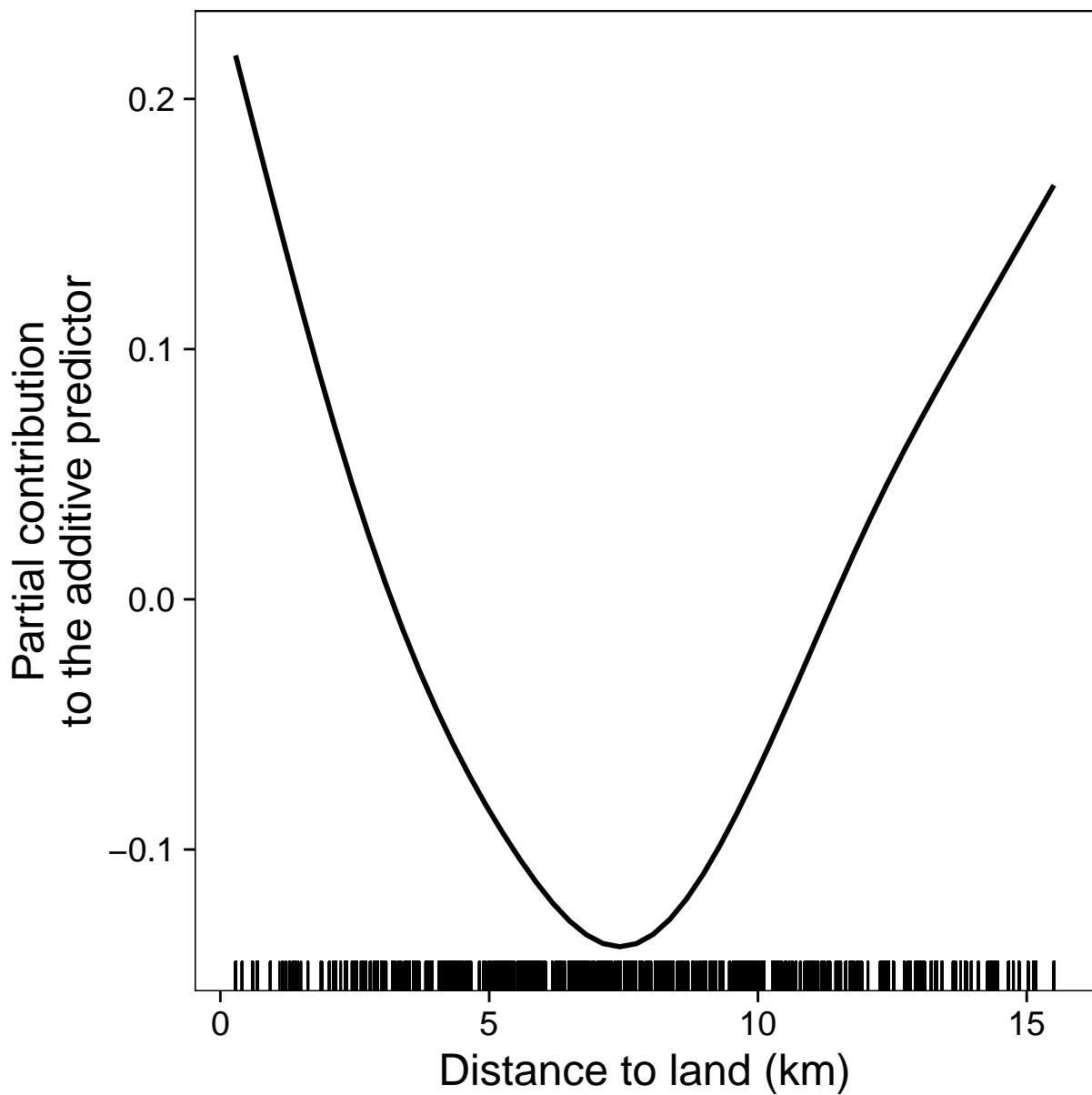


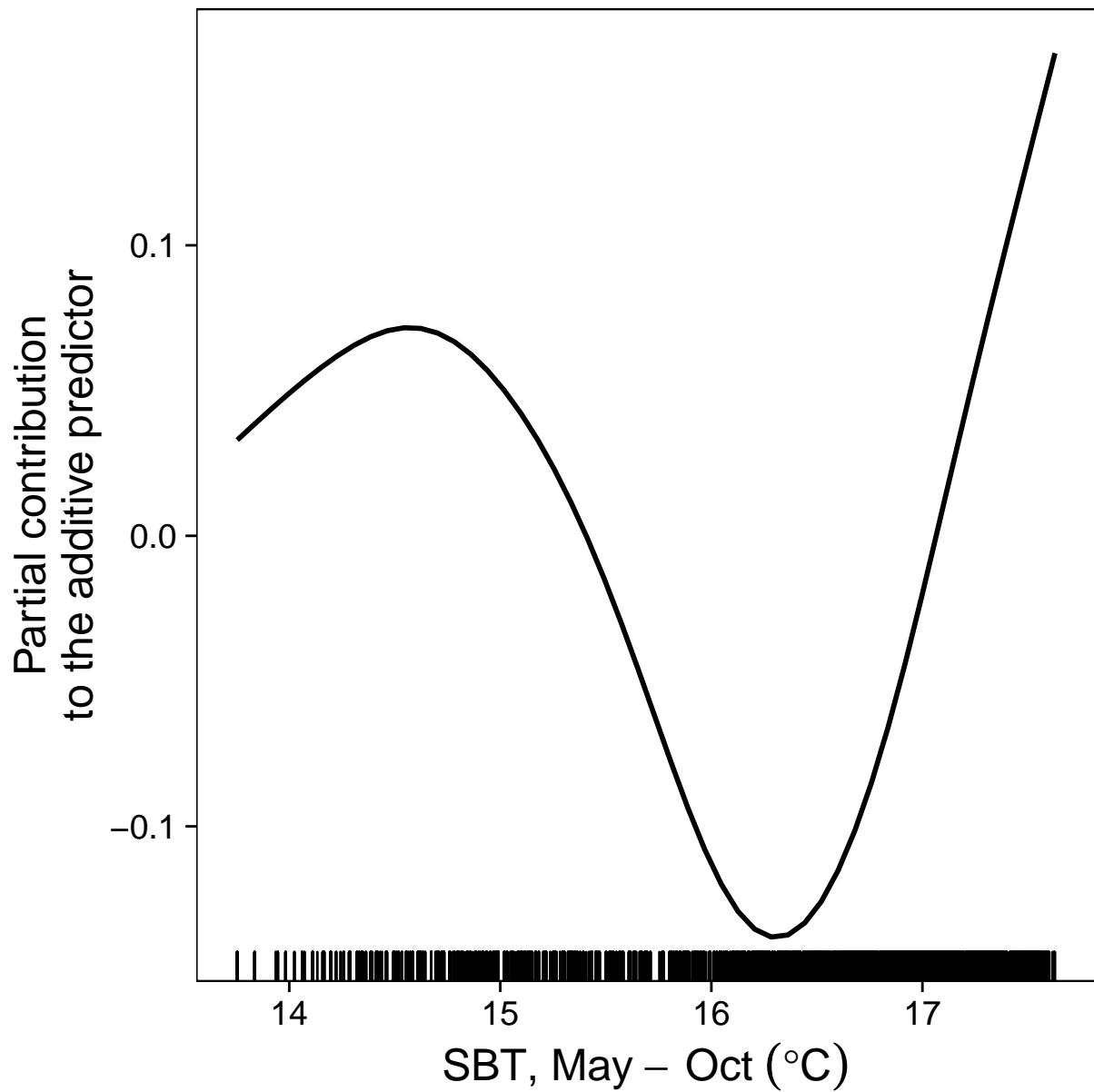


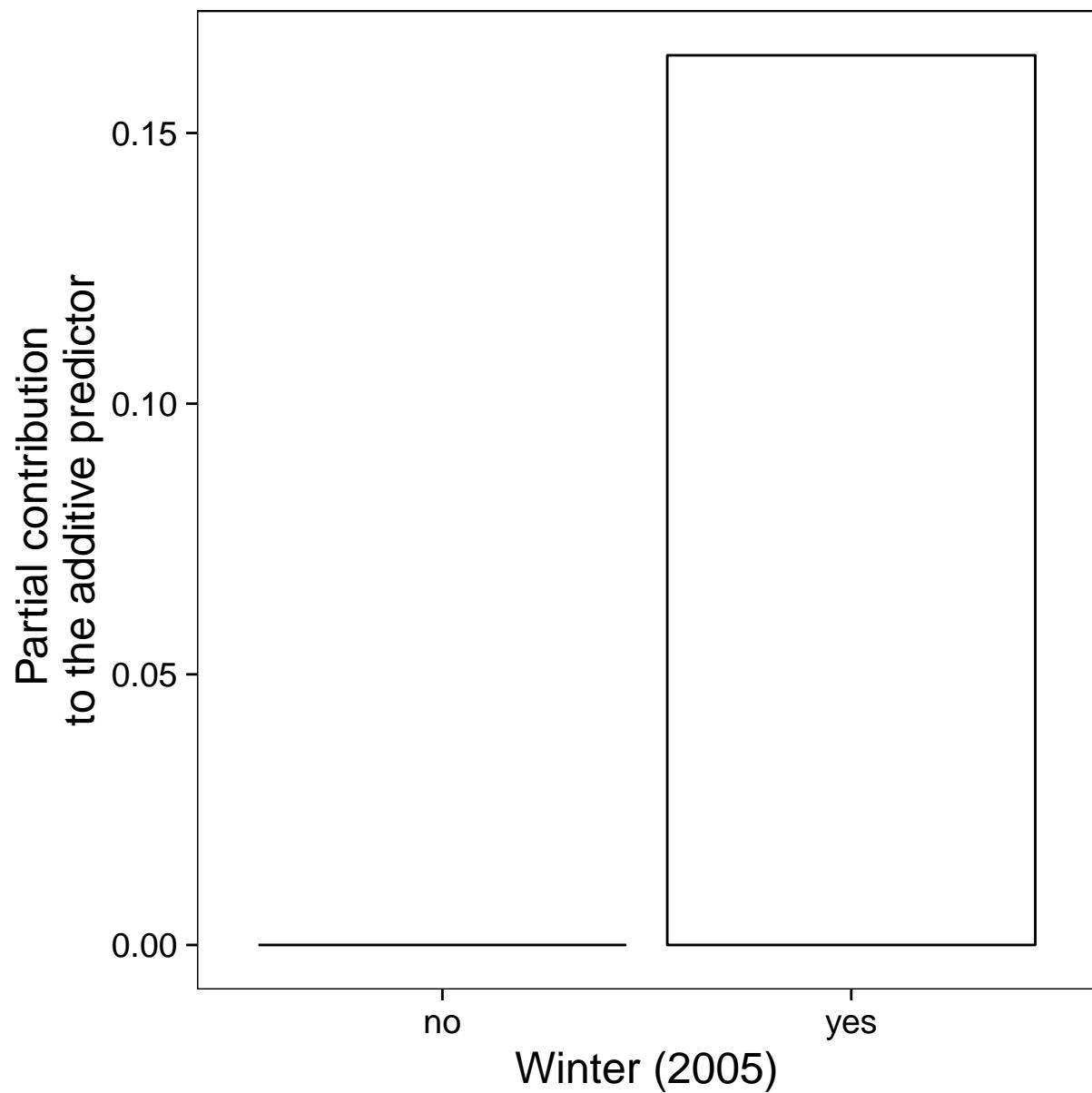




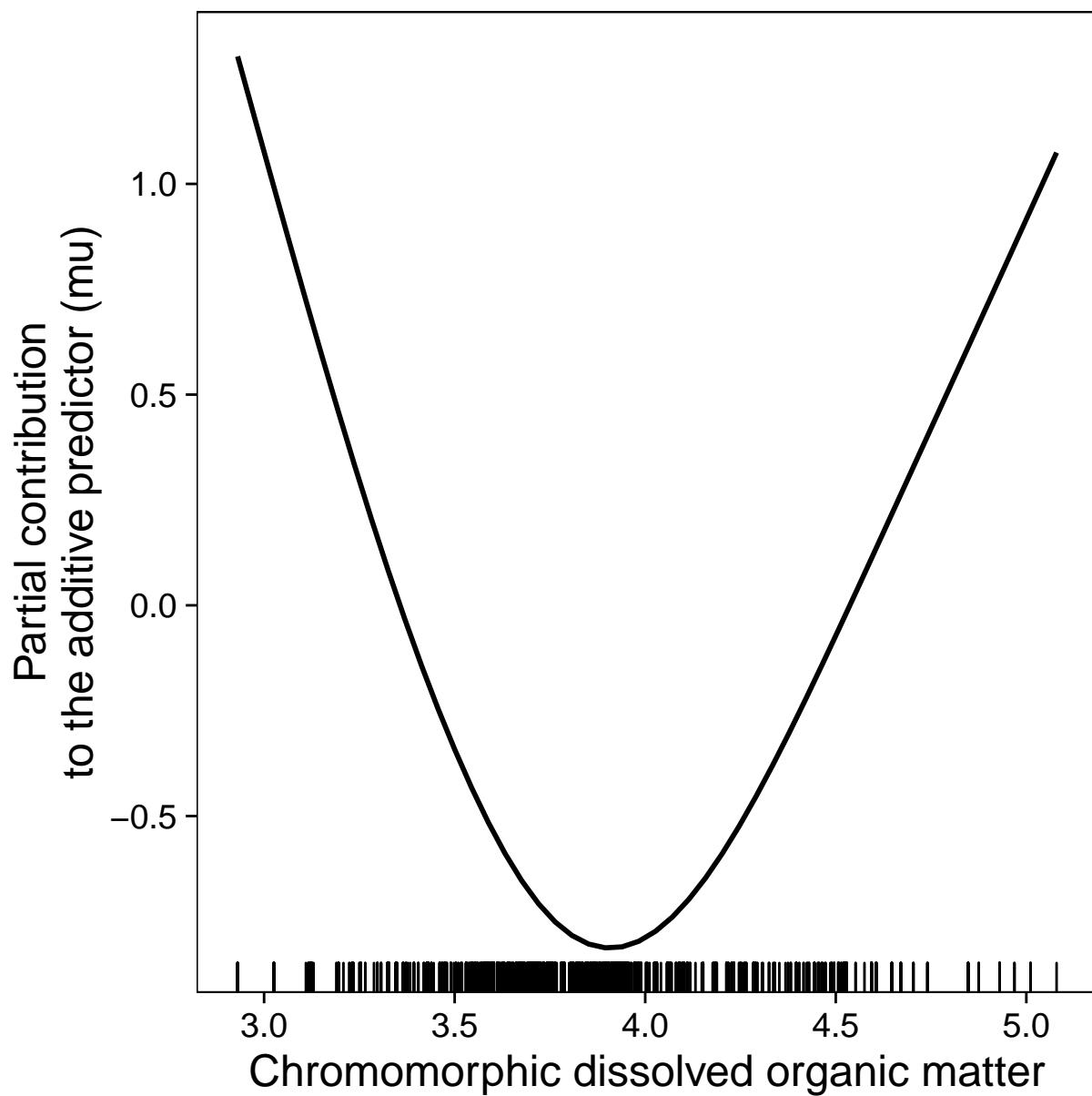


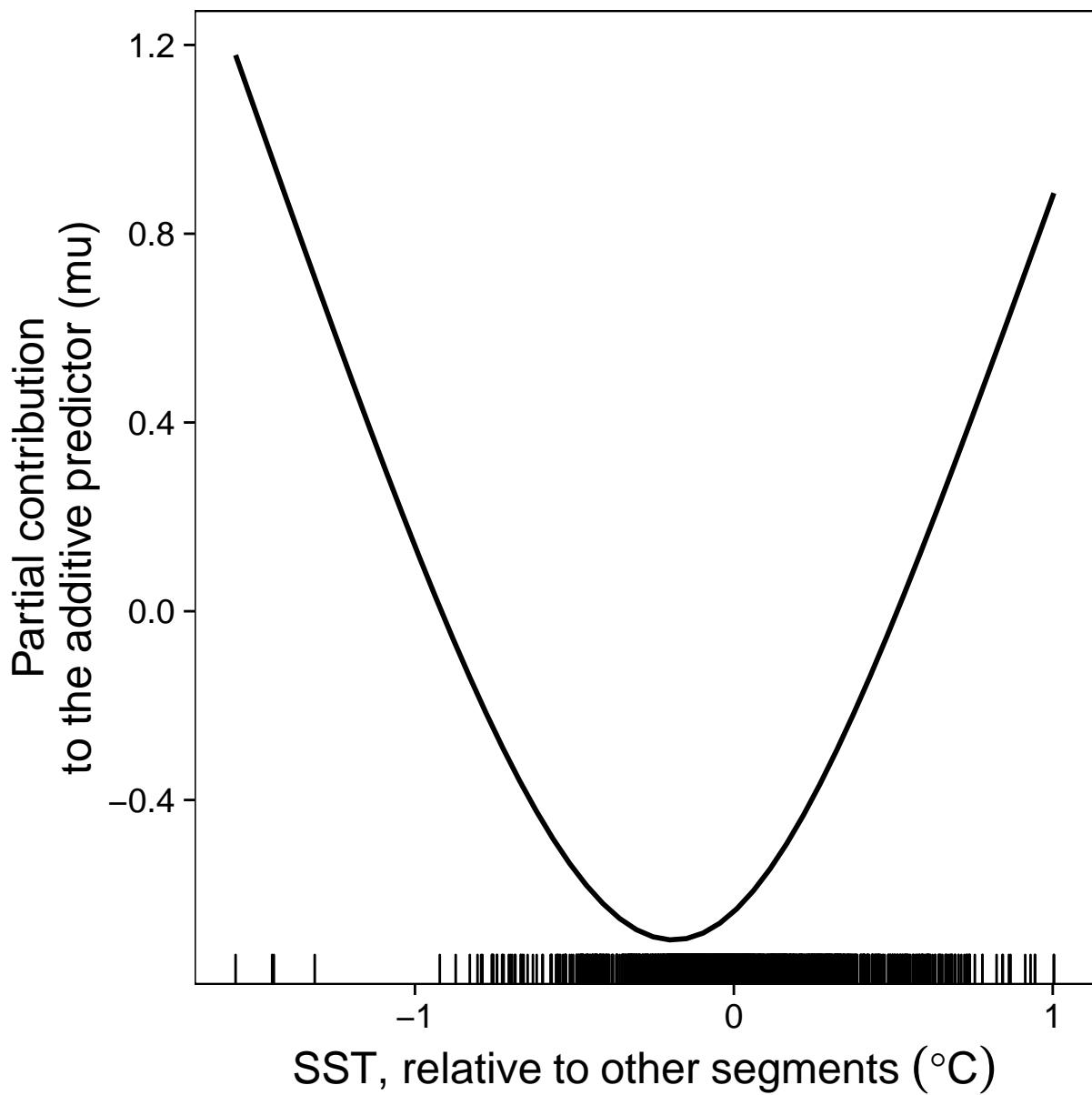


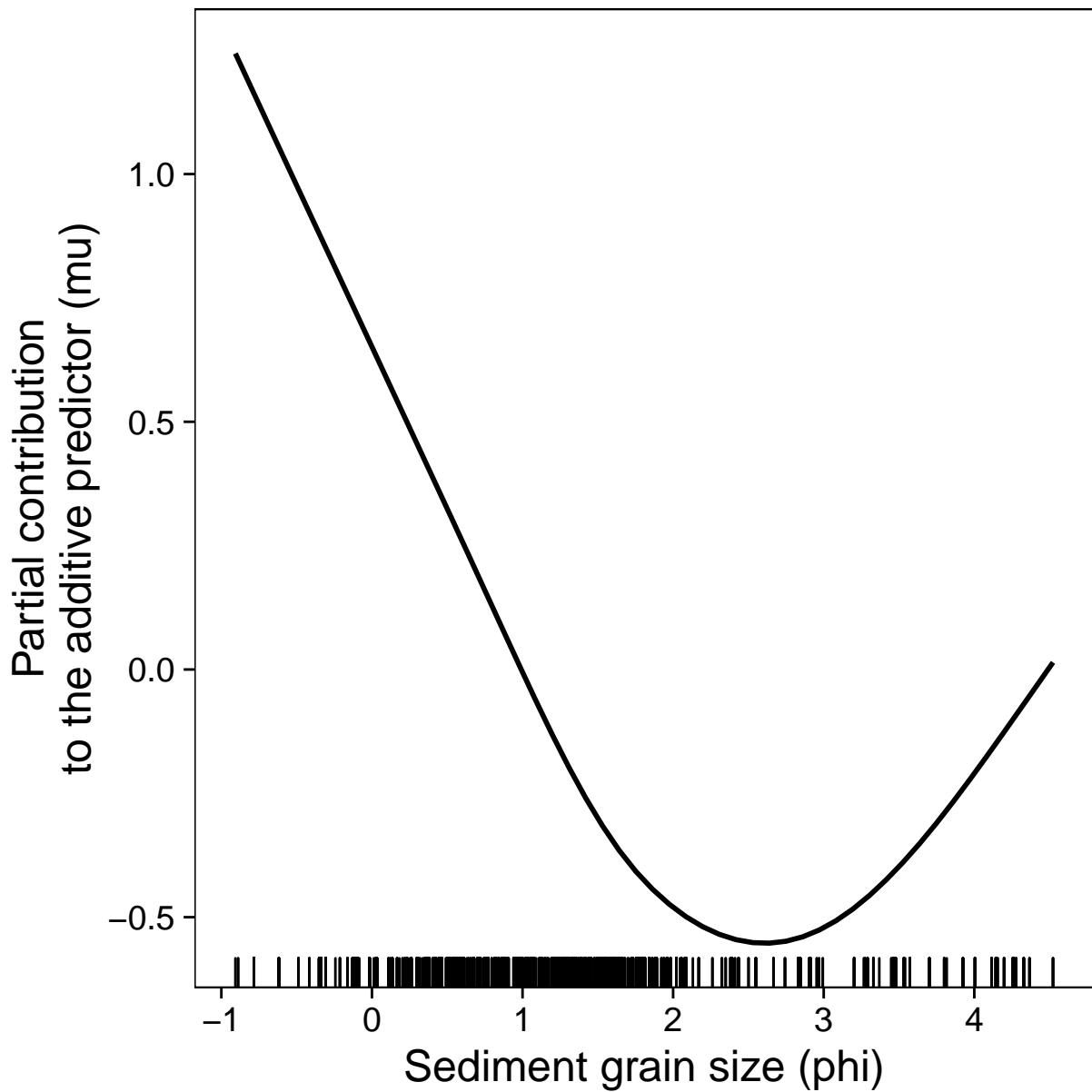


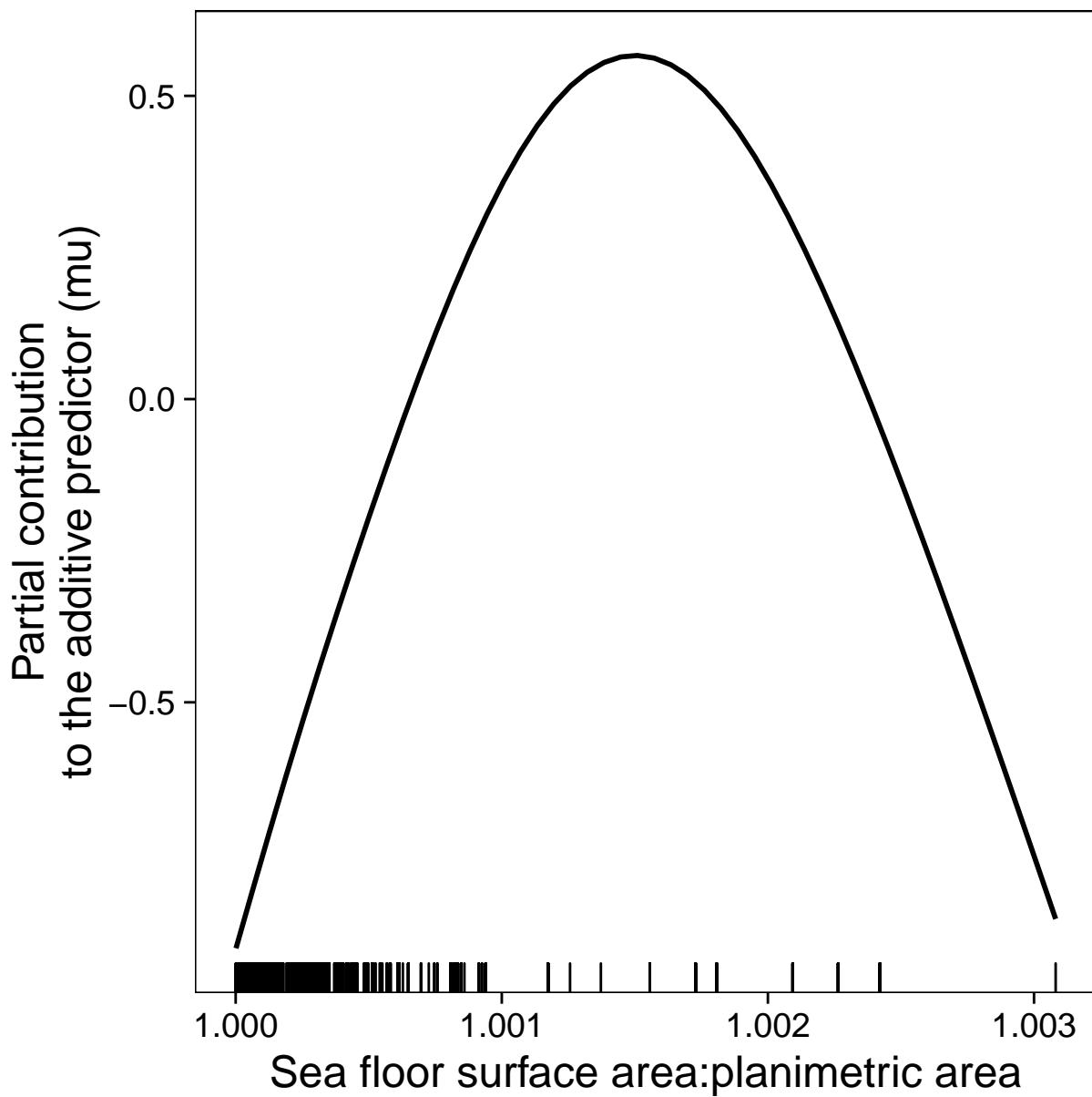


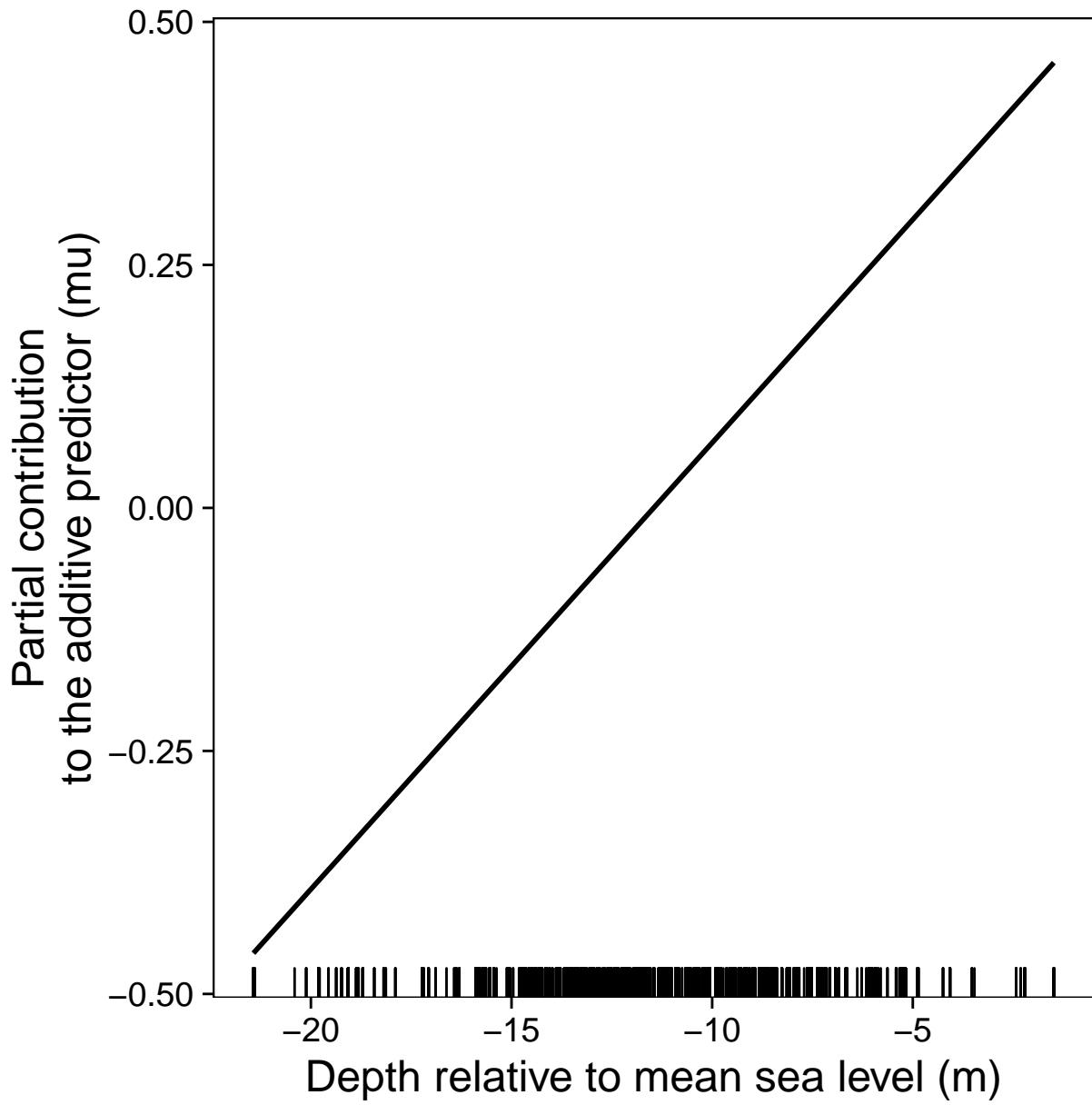
Conditional mean

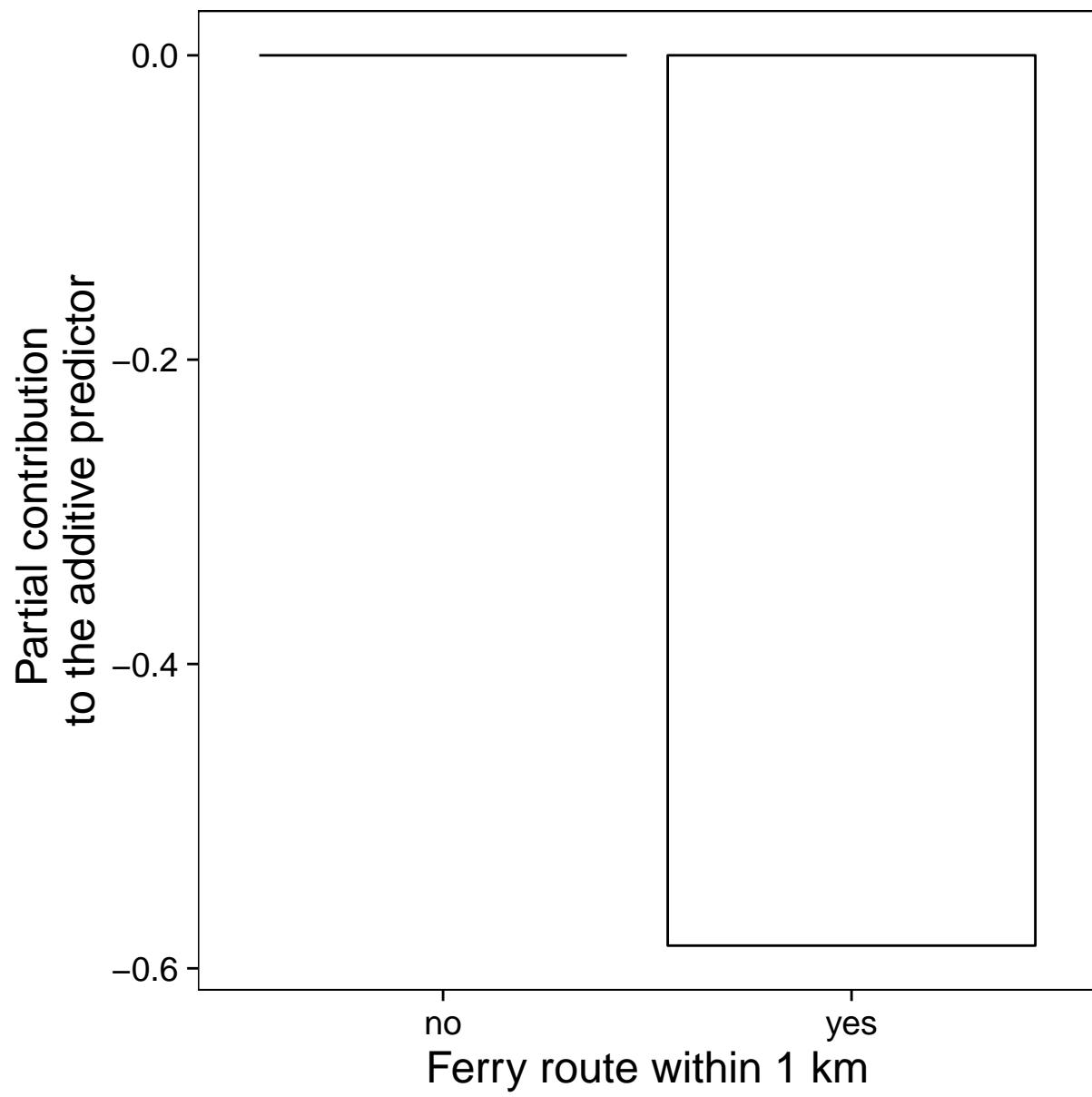




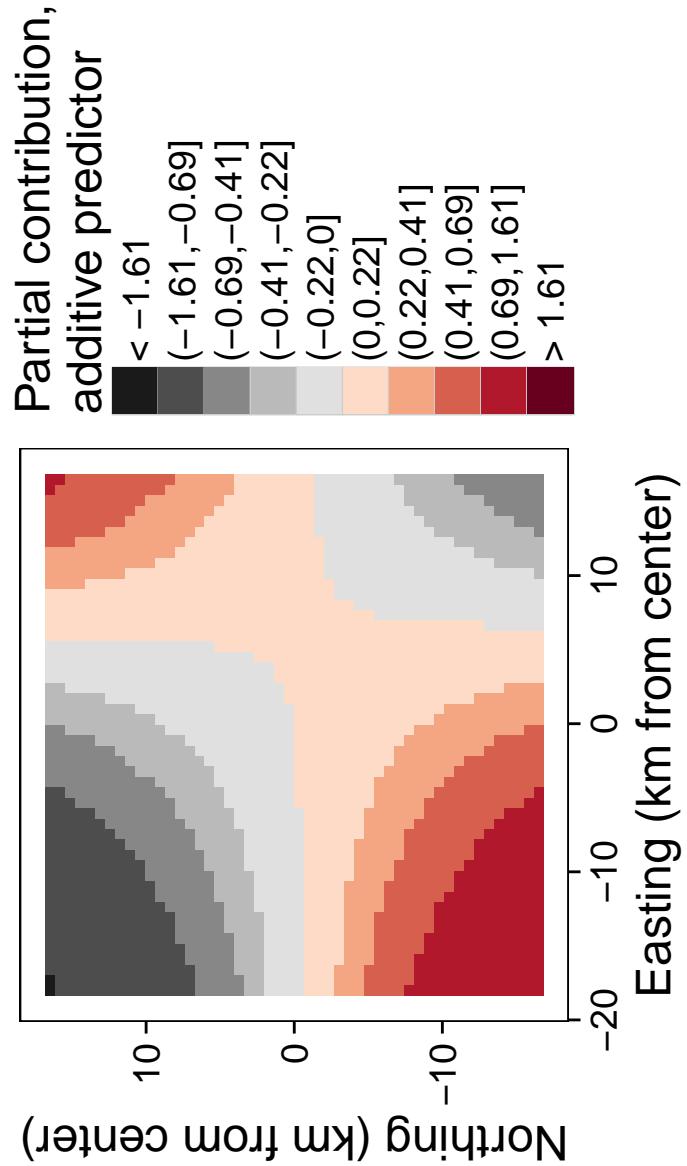


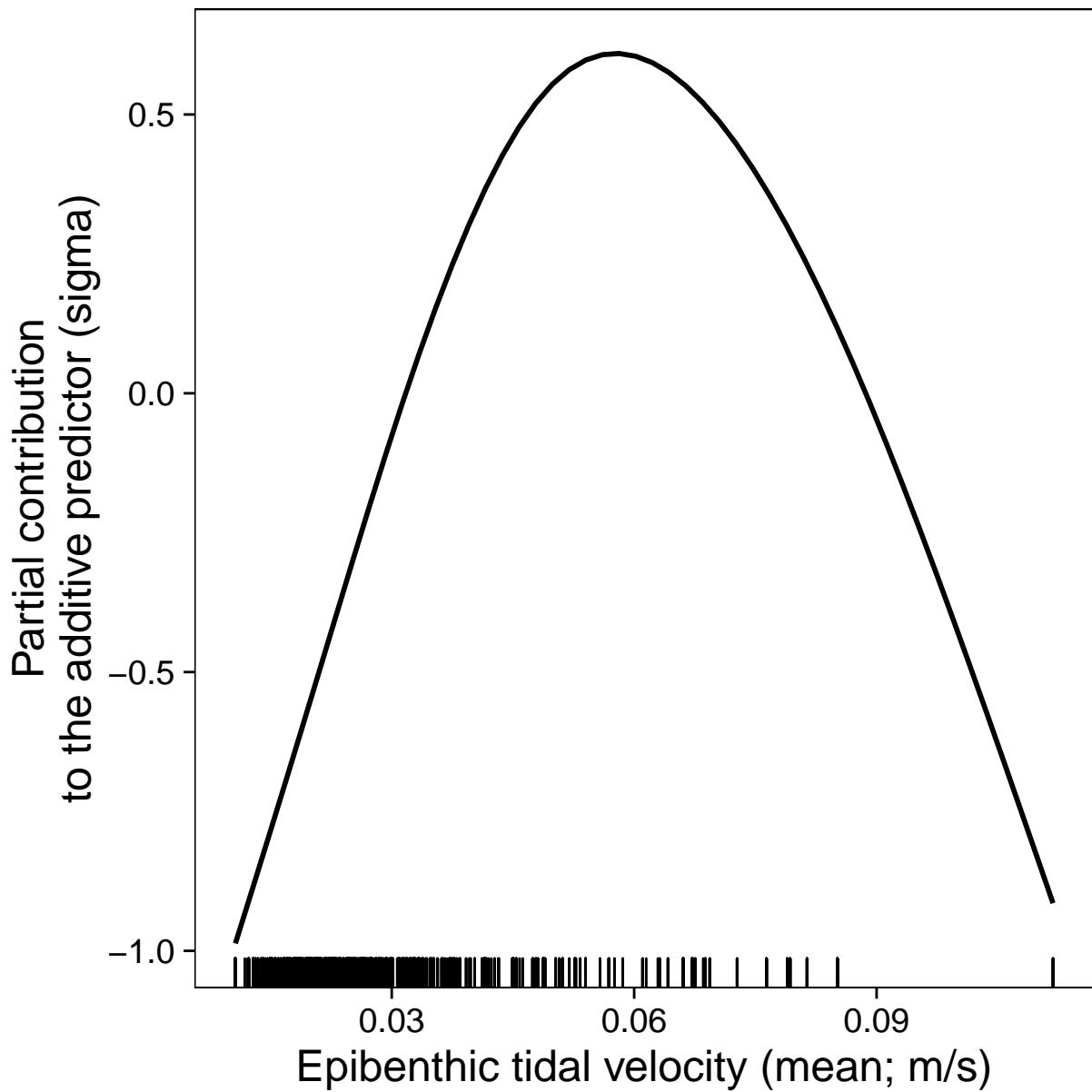


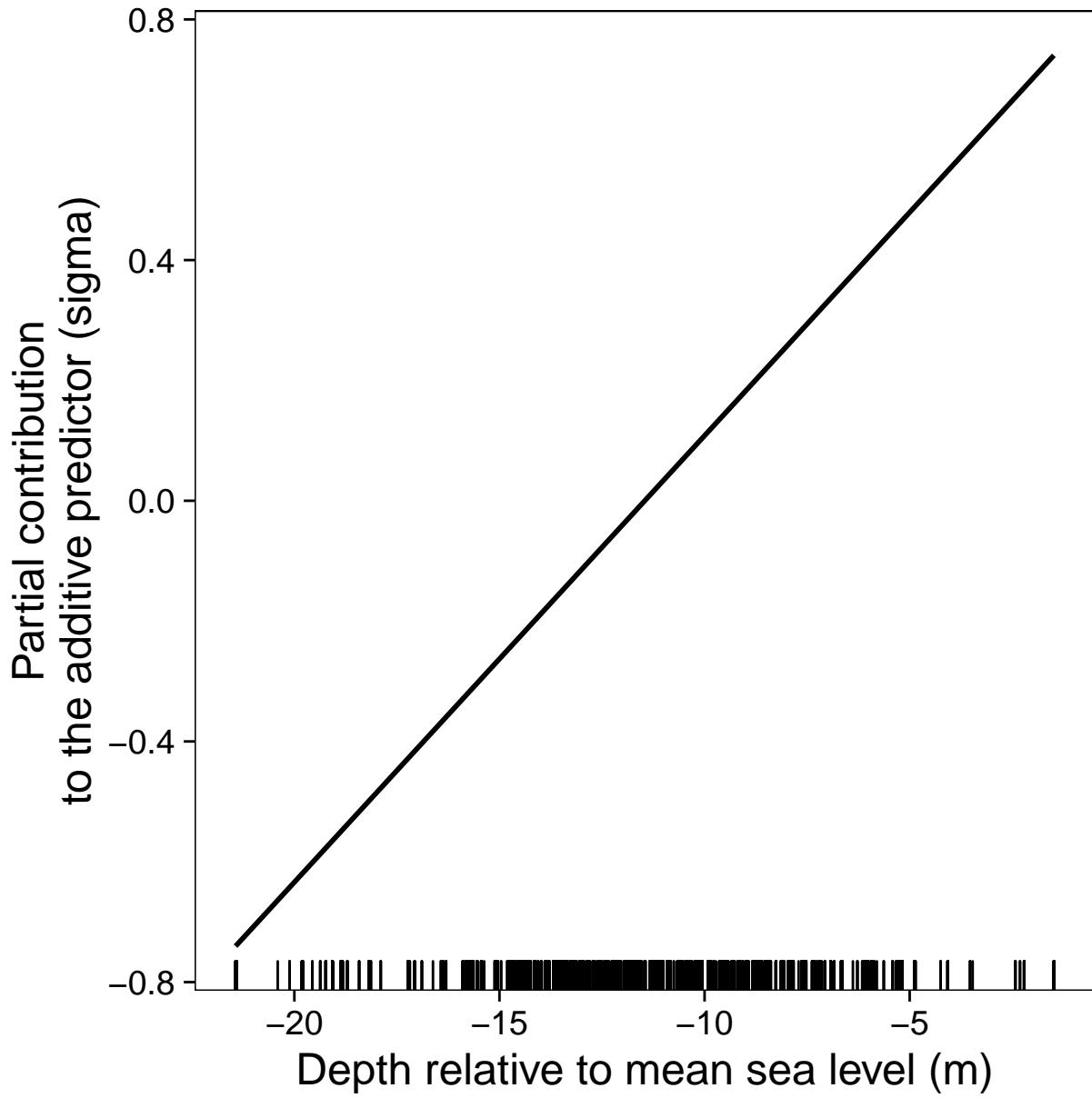


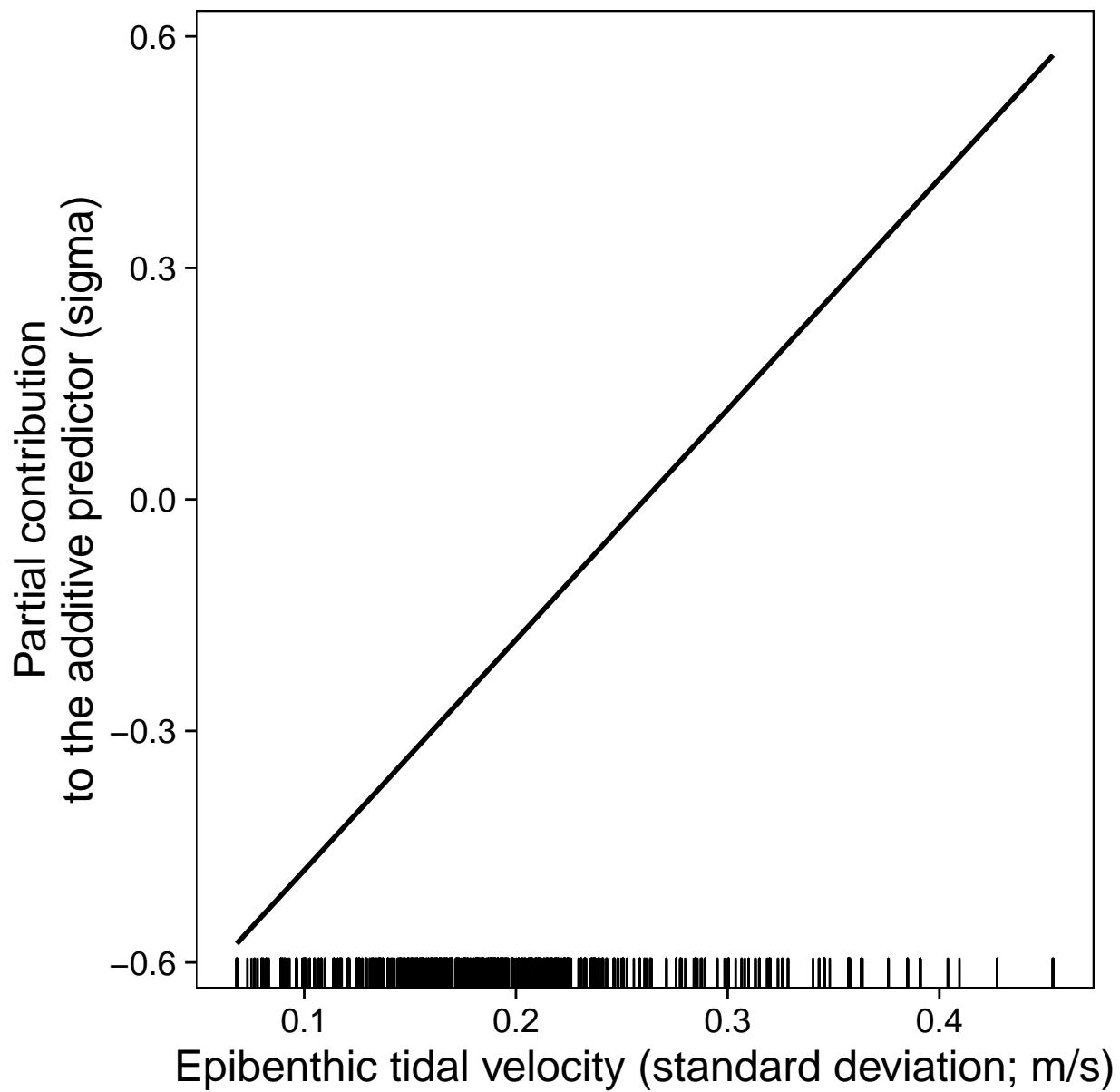


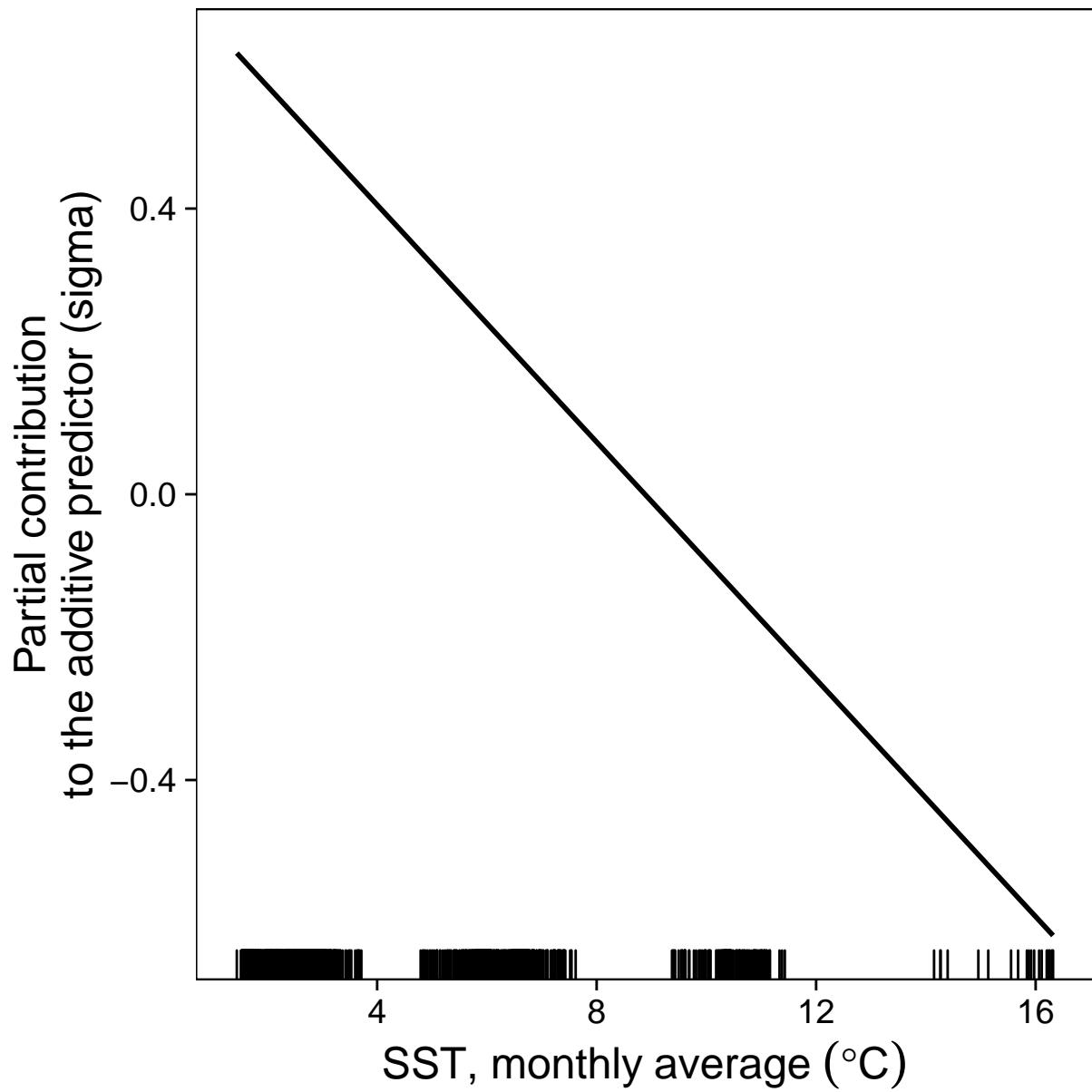
Conditional overdispersion

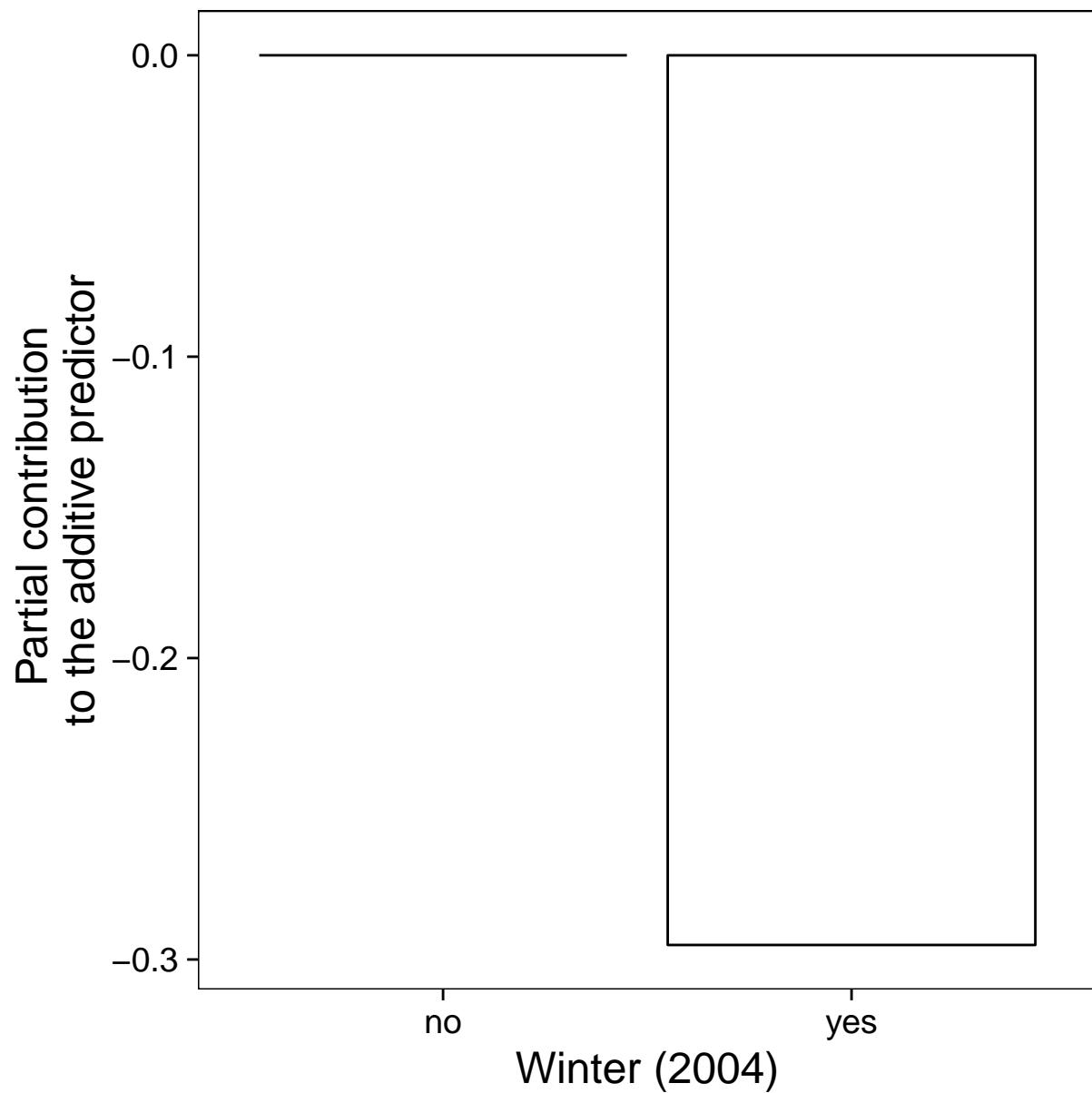








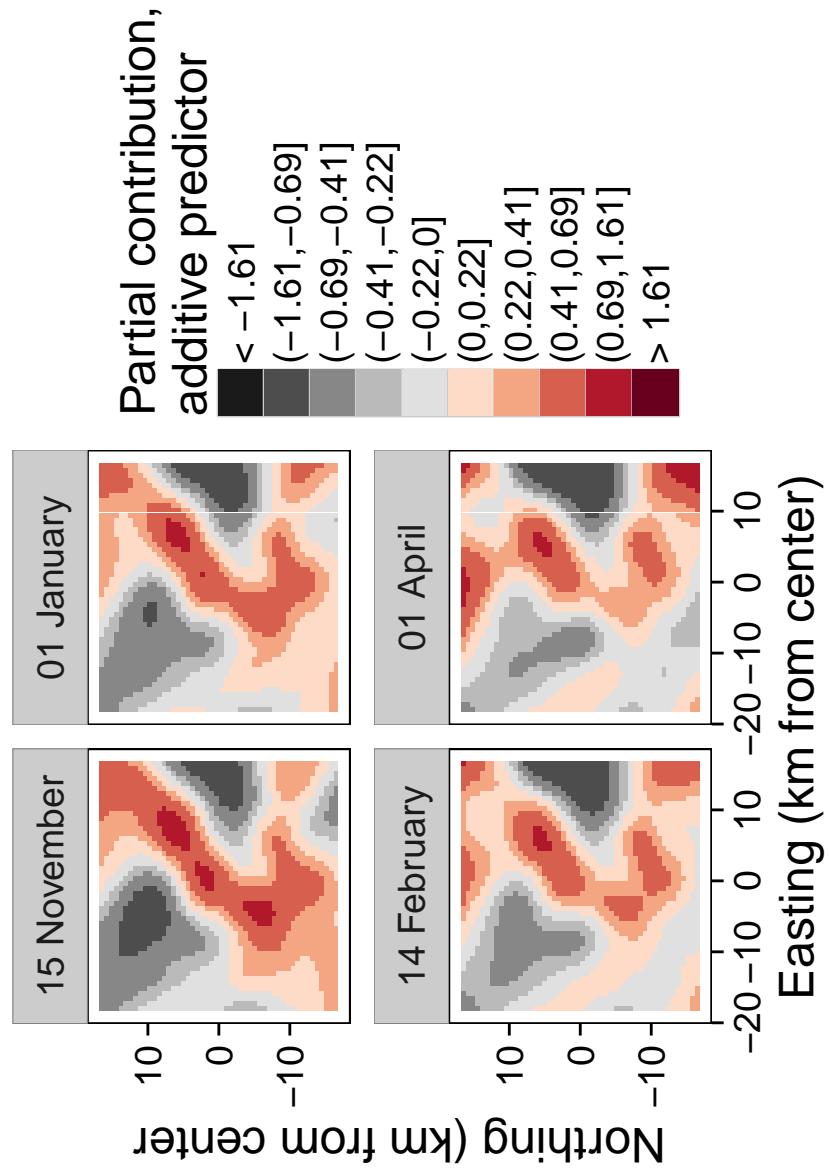


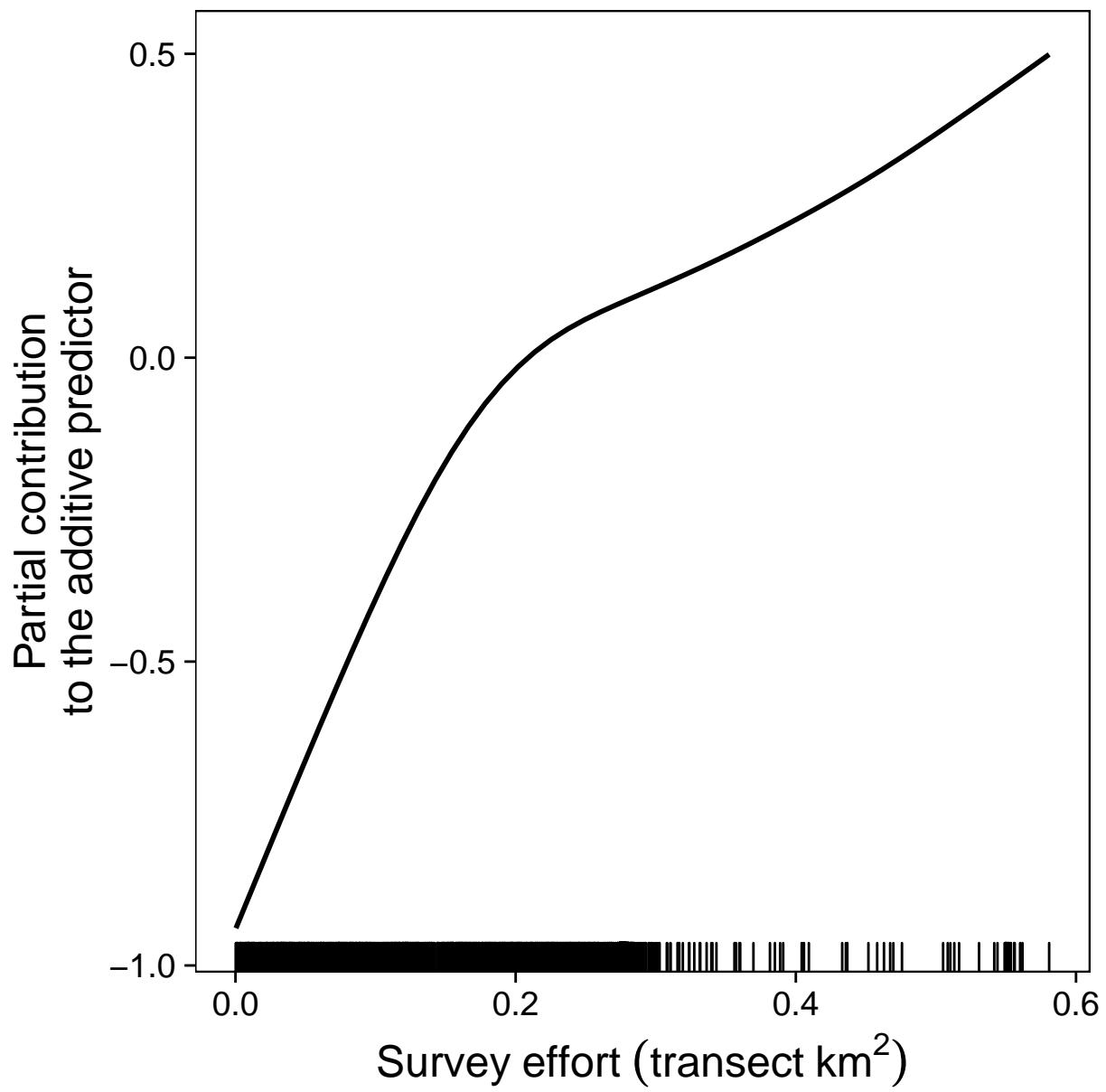


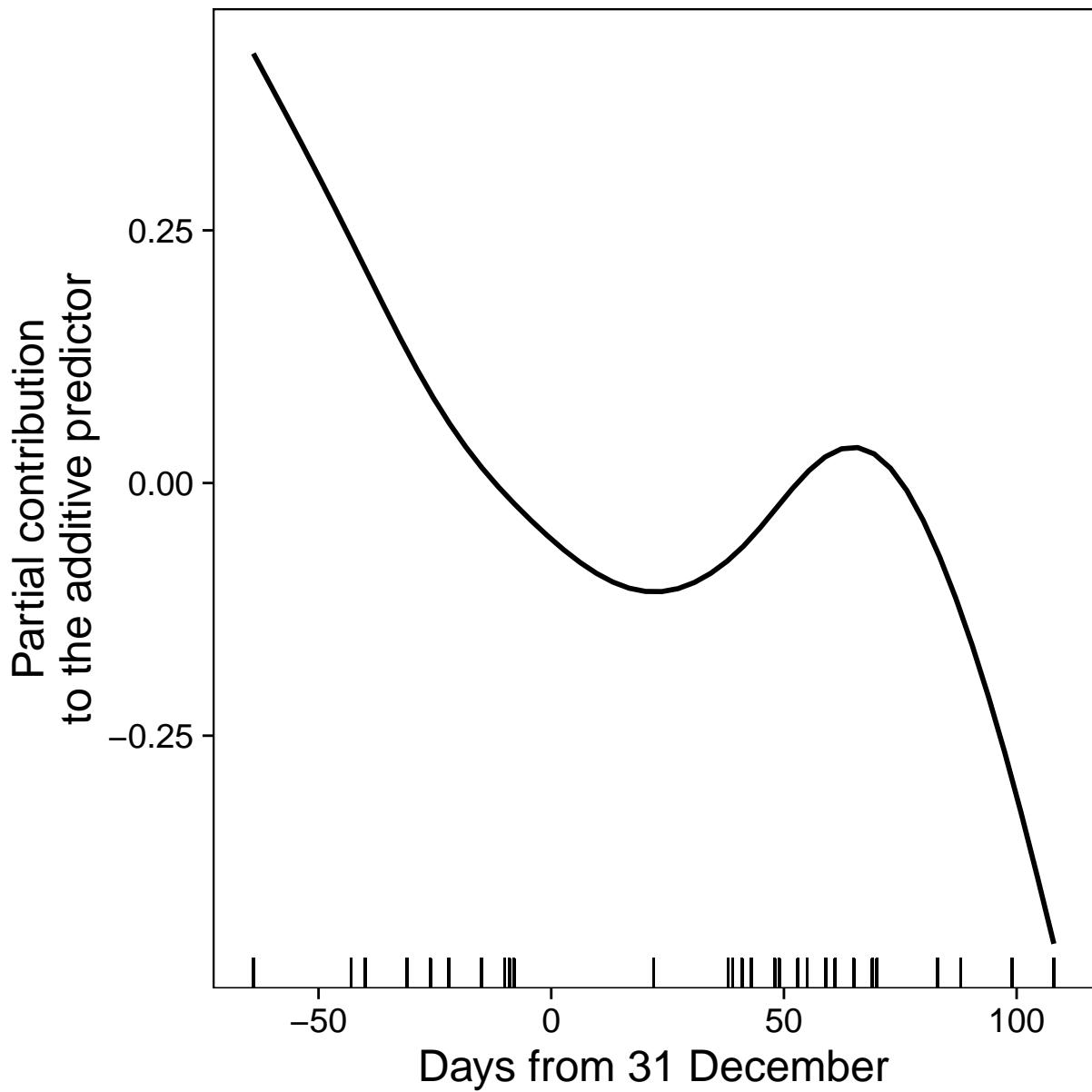
Appendix 6. Scoter stable covariate effects

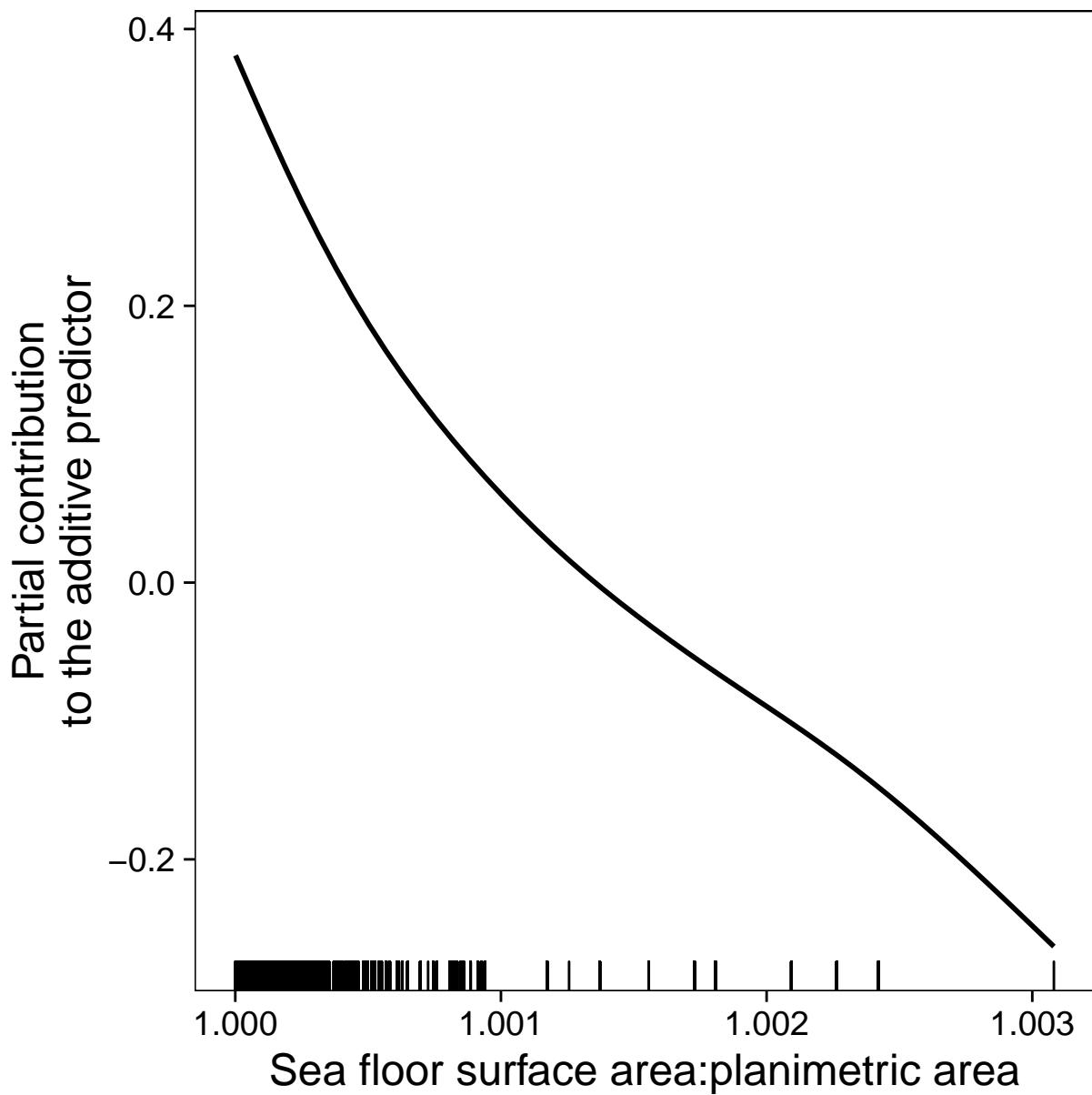
Marginal functional plots of the relationships between covariates (controlling for all other variables; i.e., at their mean values) and the occupancy, conditional mean abundance, and conditional overdispersion of abundance of scoters (Black, Surf, and White-winged Scoter) in Nantucket Sound, Massachusetts, USA. Covariate plots are ordered roughly in descending order of the magnitude of their influence on the additive predictor in each model (or model parameter for count models). Vertical lines along the x -axis (i.e., rug plots) indicate observed covariate values. Covariates (and any abbreviations) are defined in detail in Appendix 2; only effects selected to be stable (see Appendix 1) are depicted.

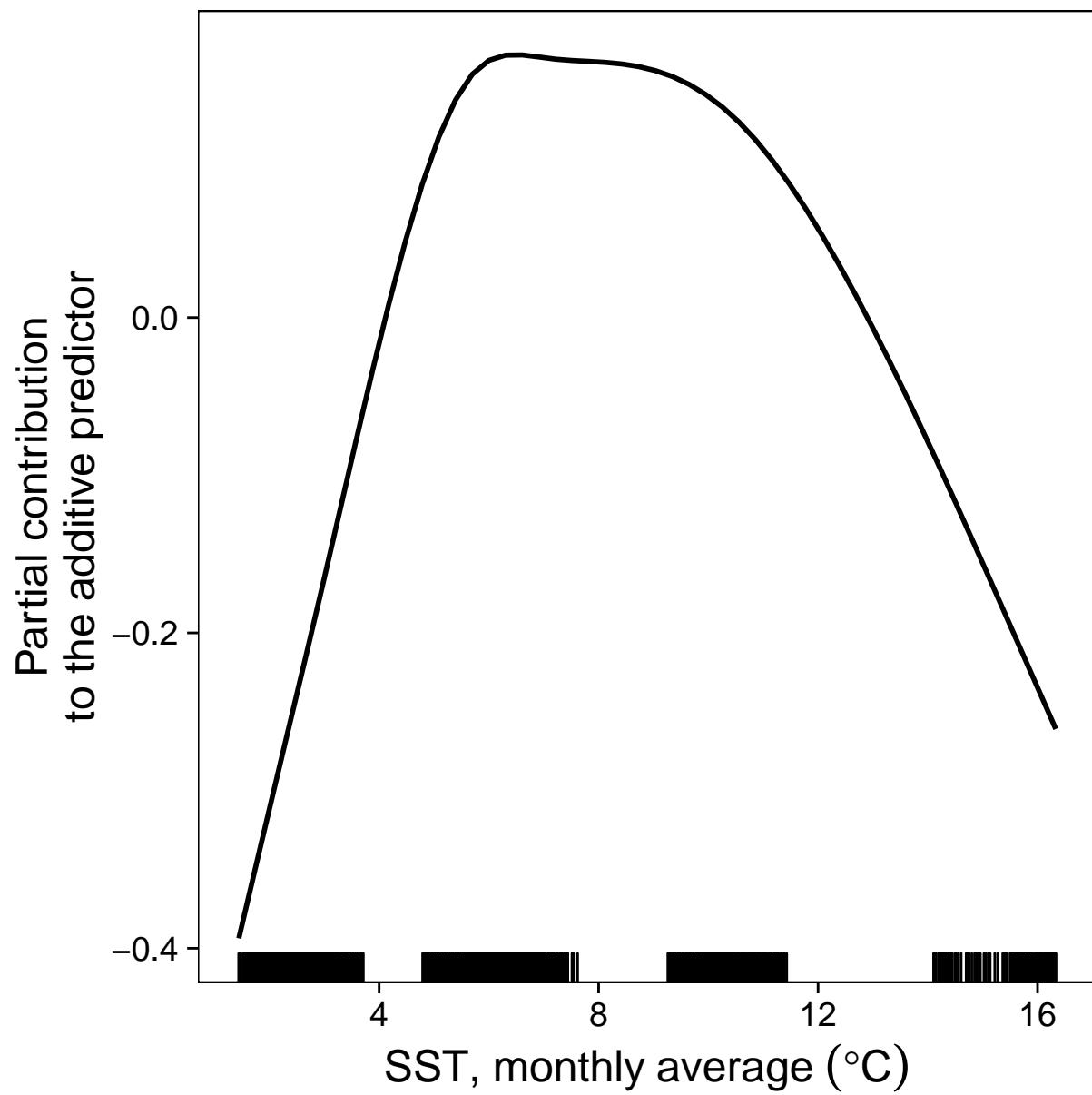
Occupancy

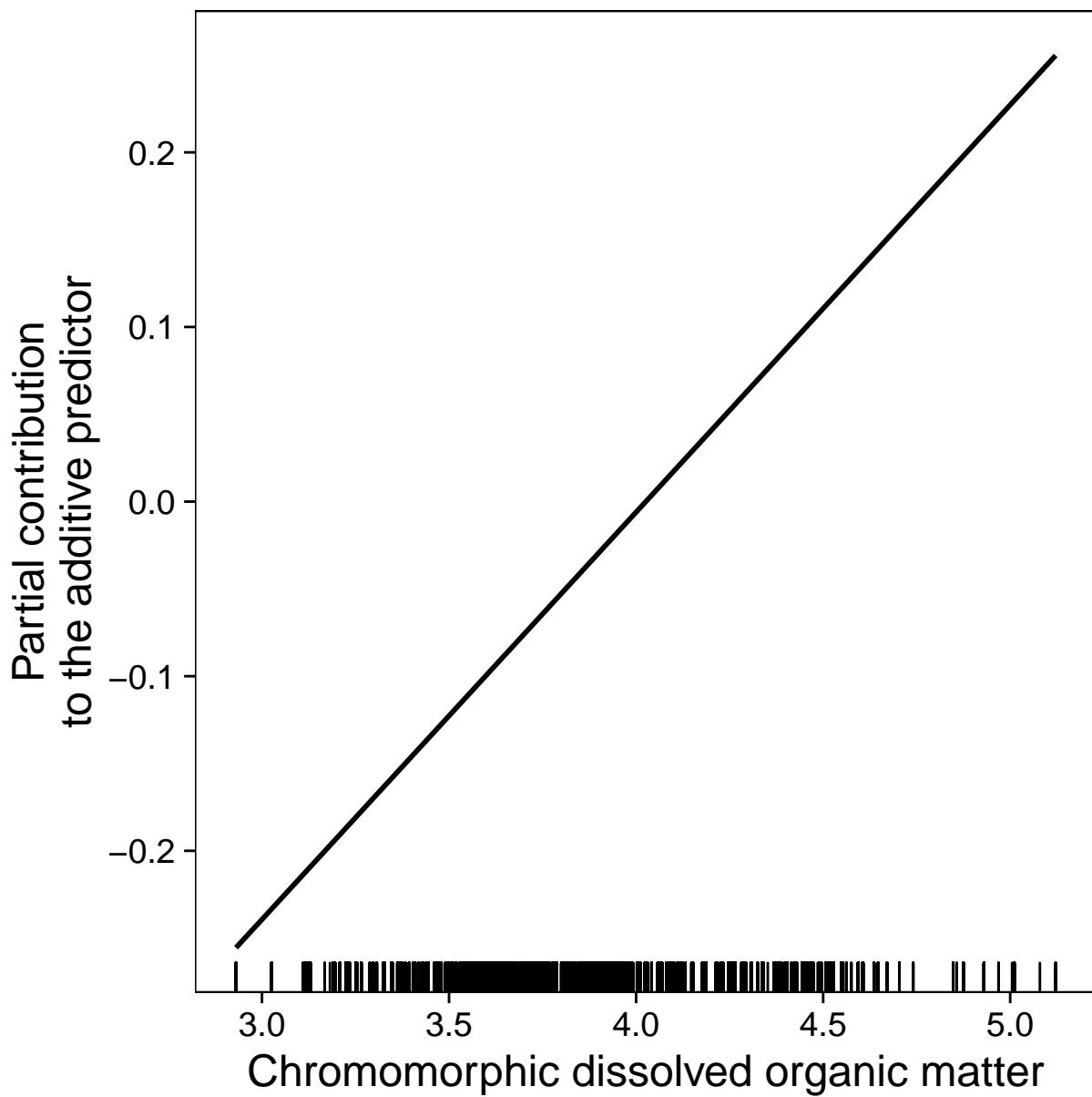


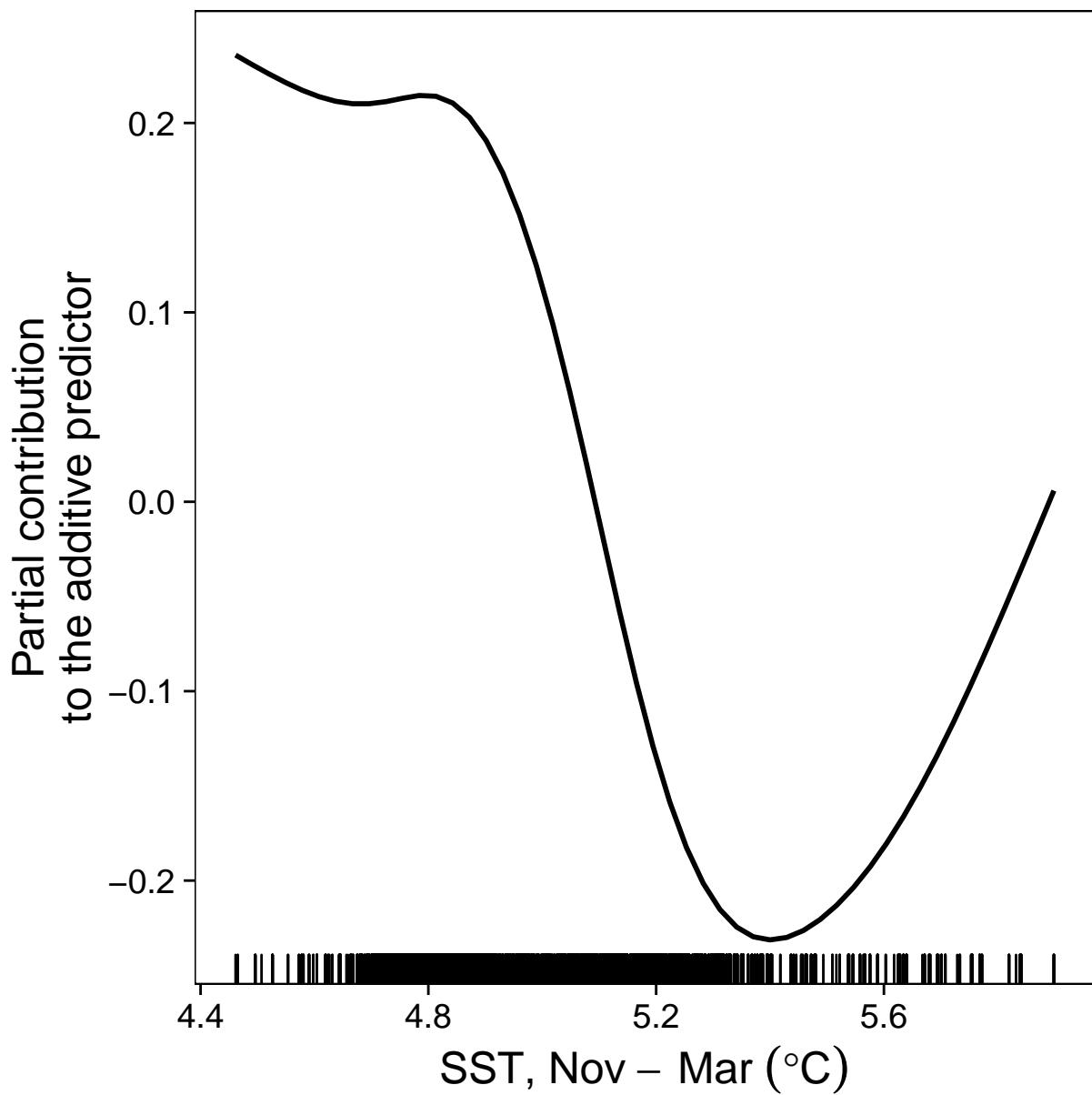


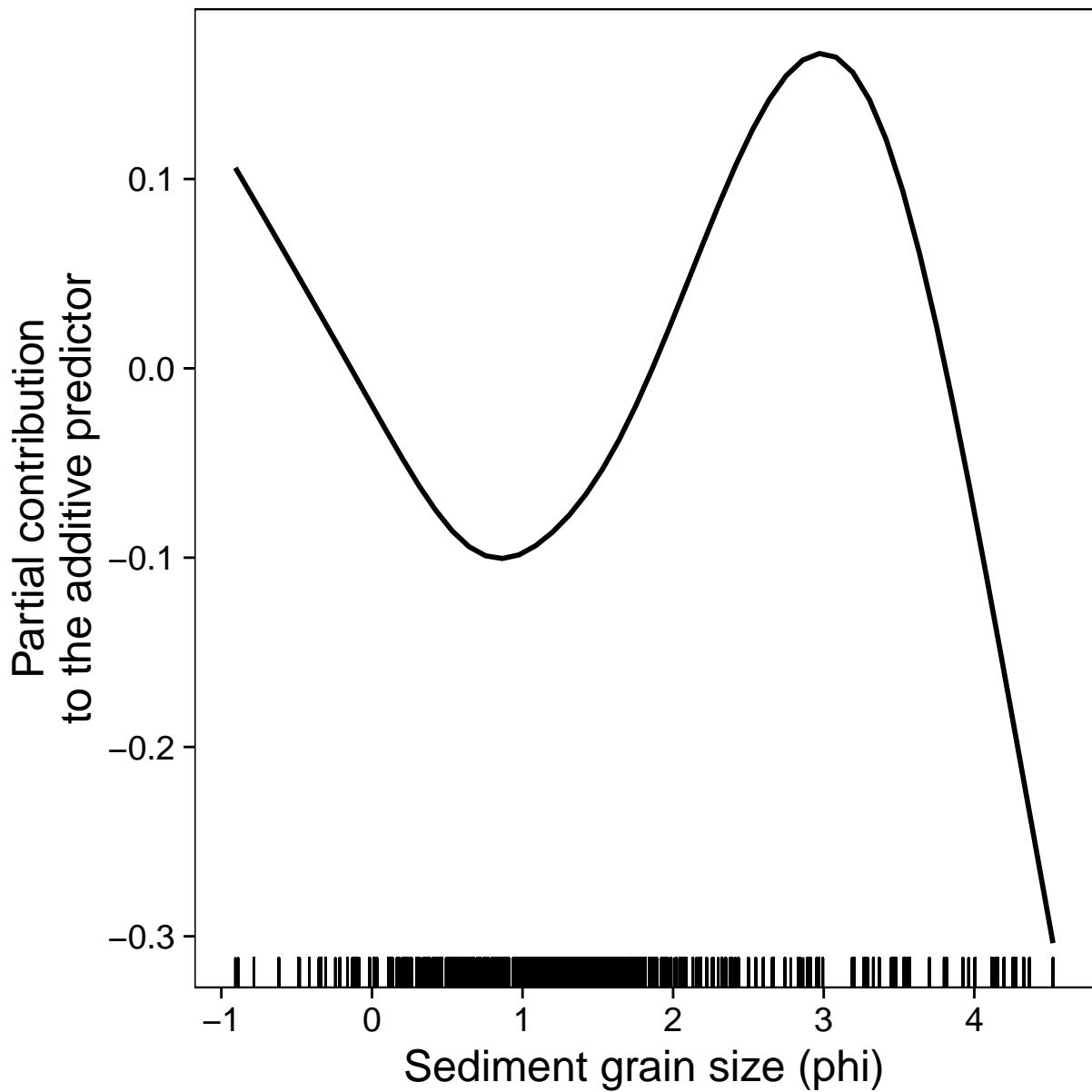


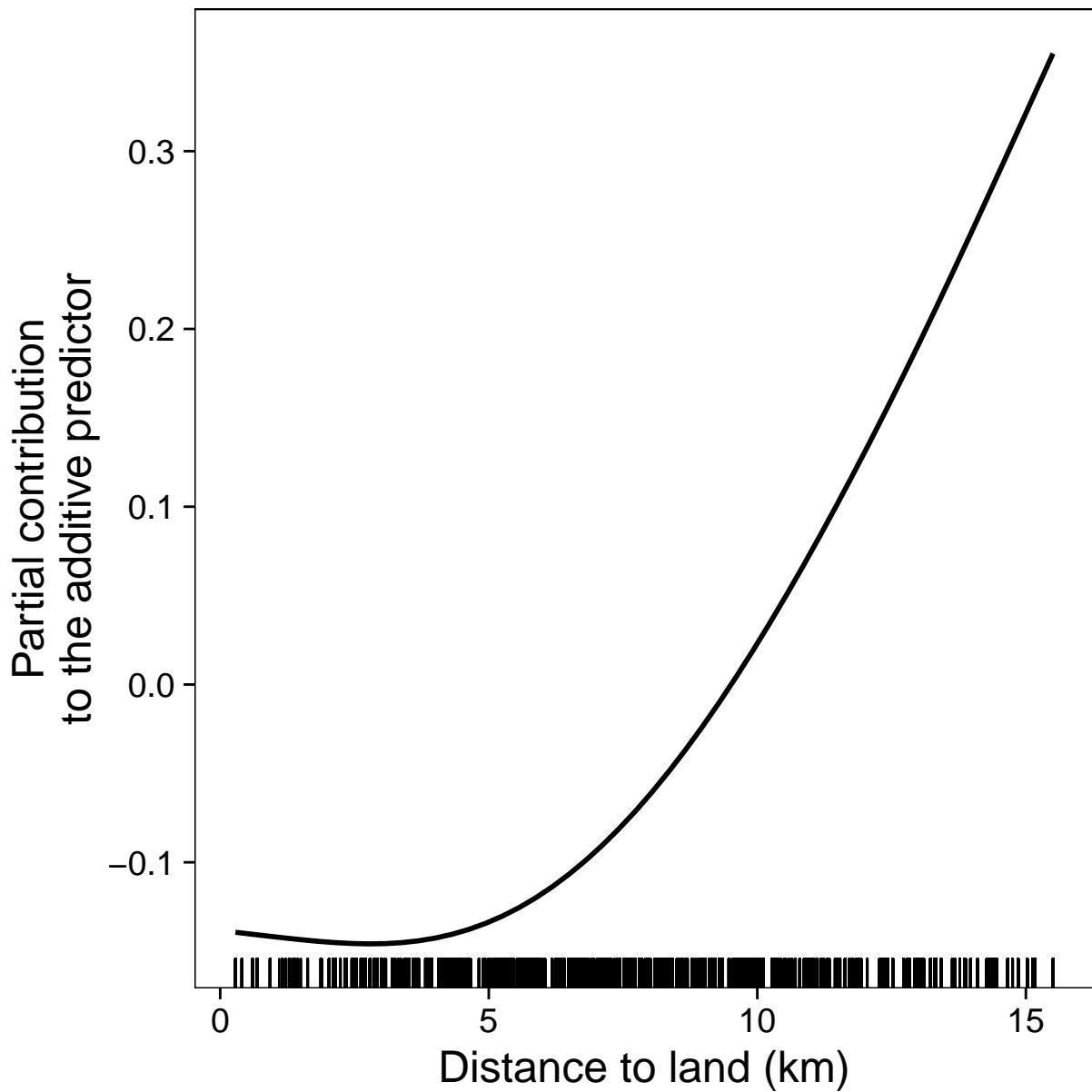


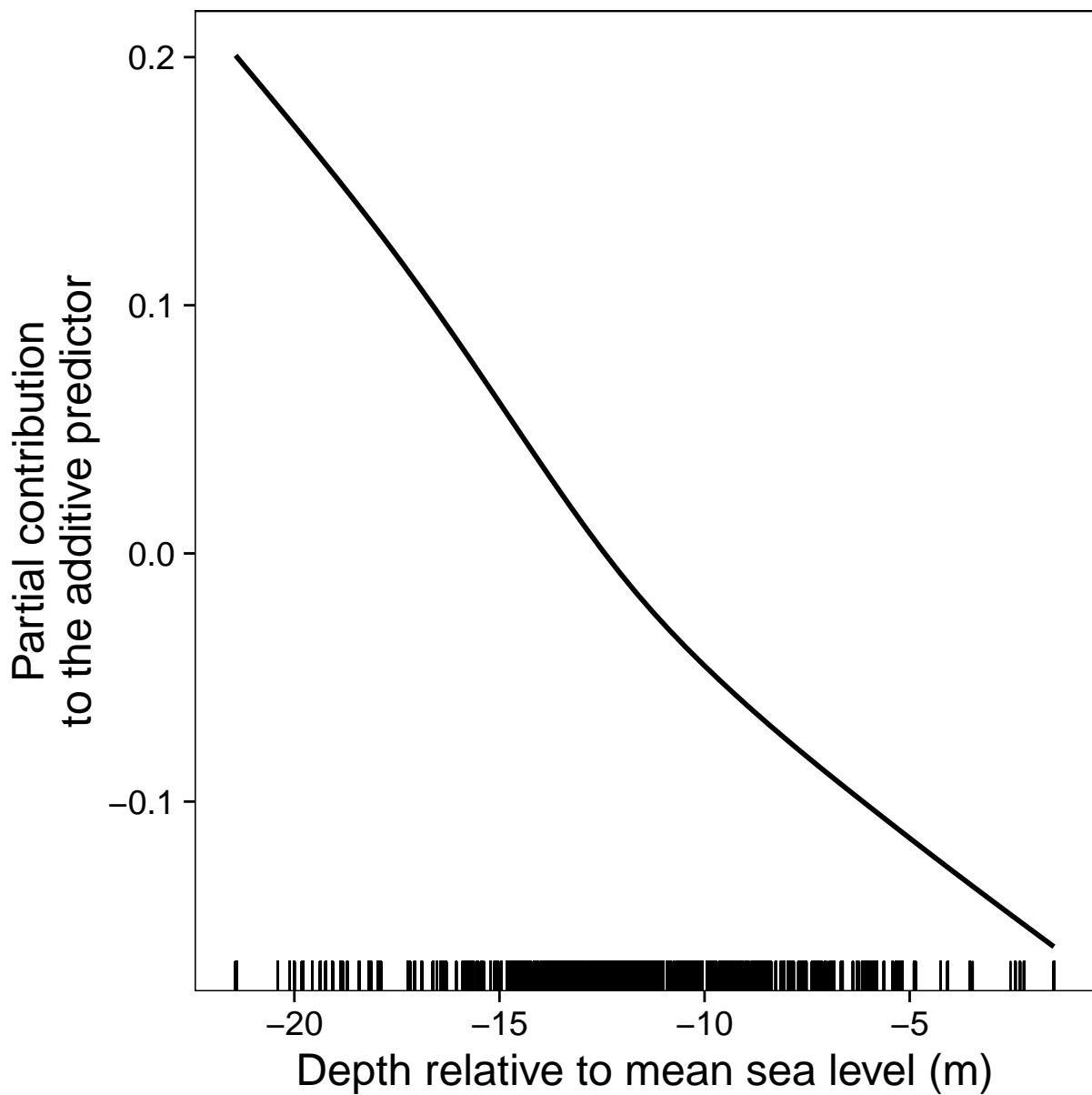


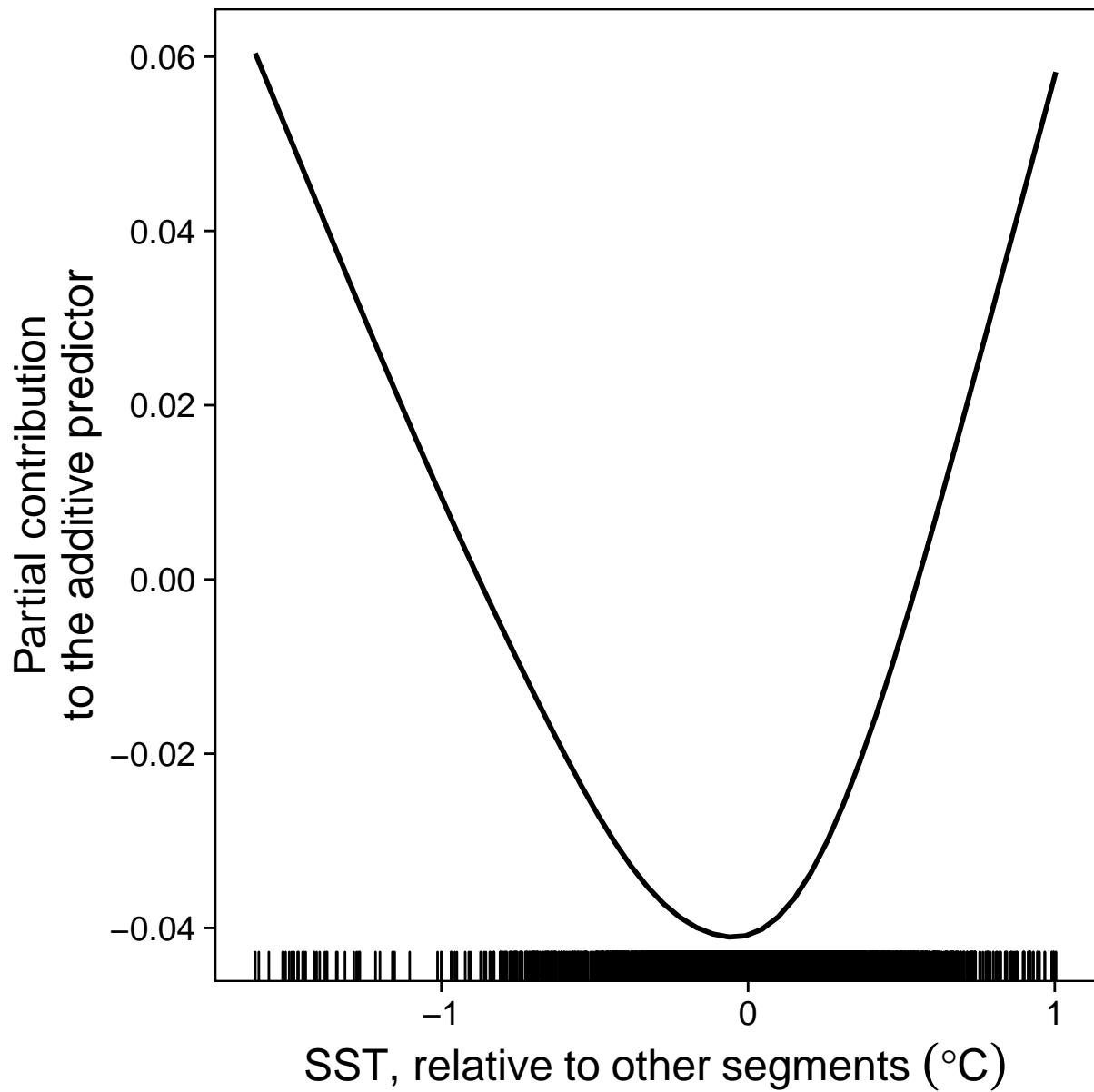




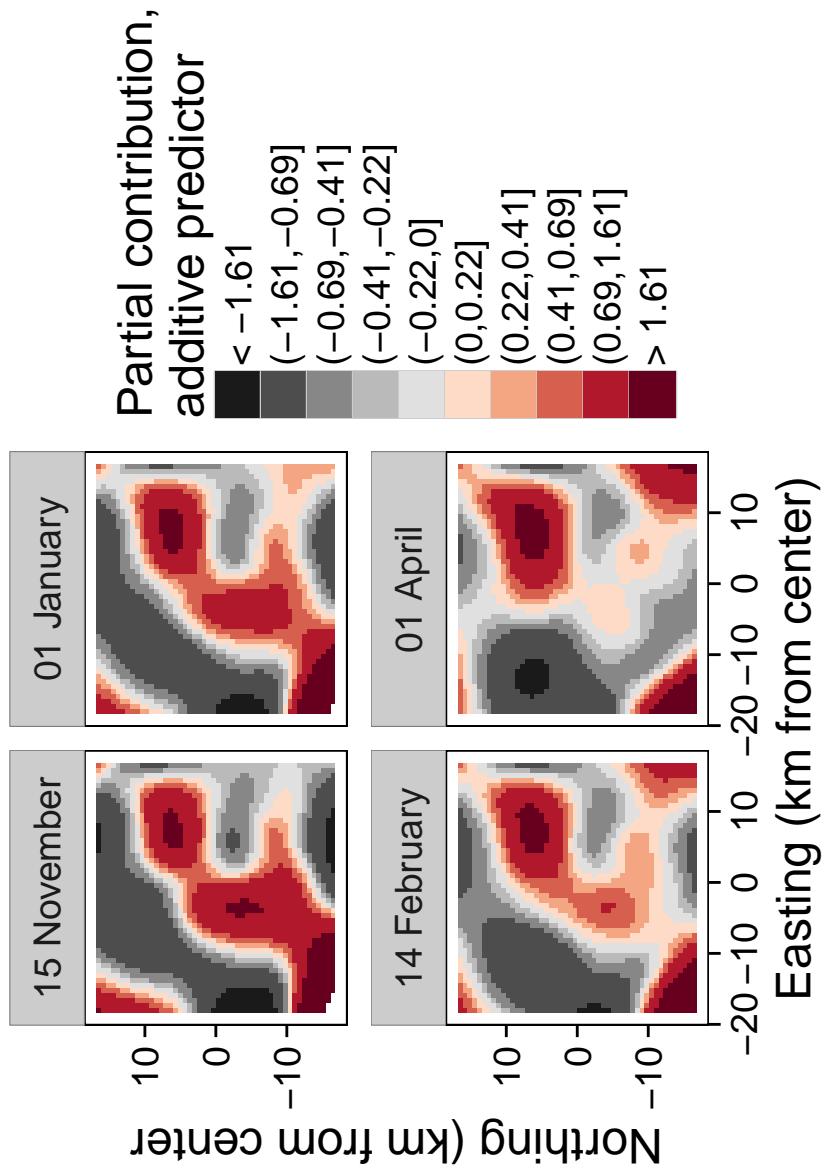


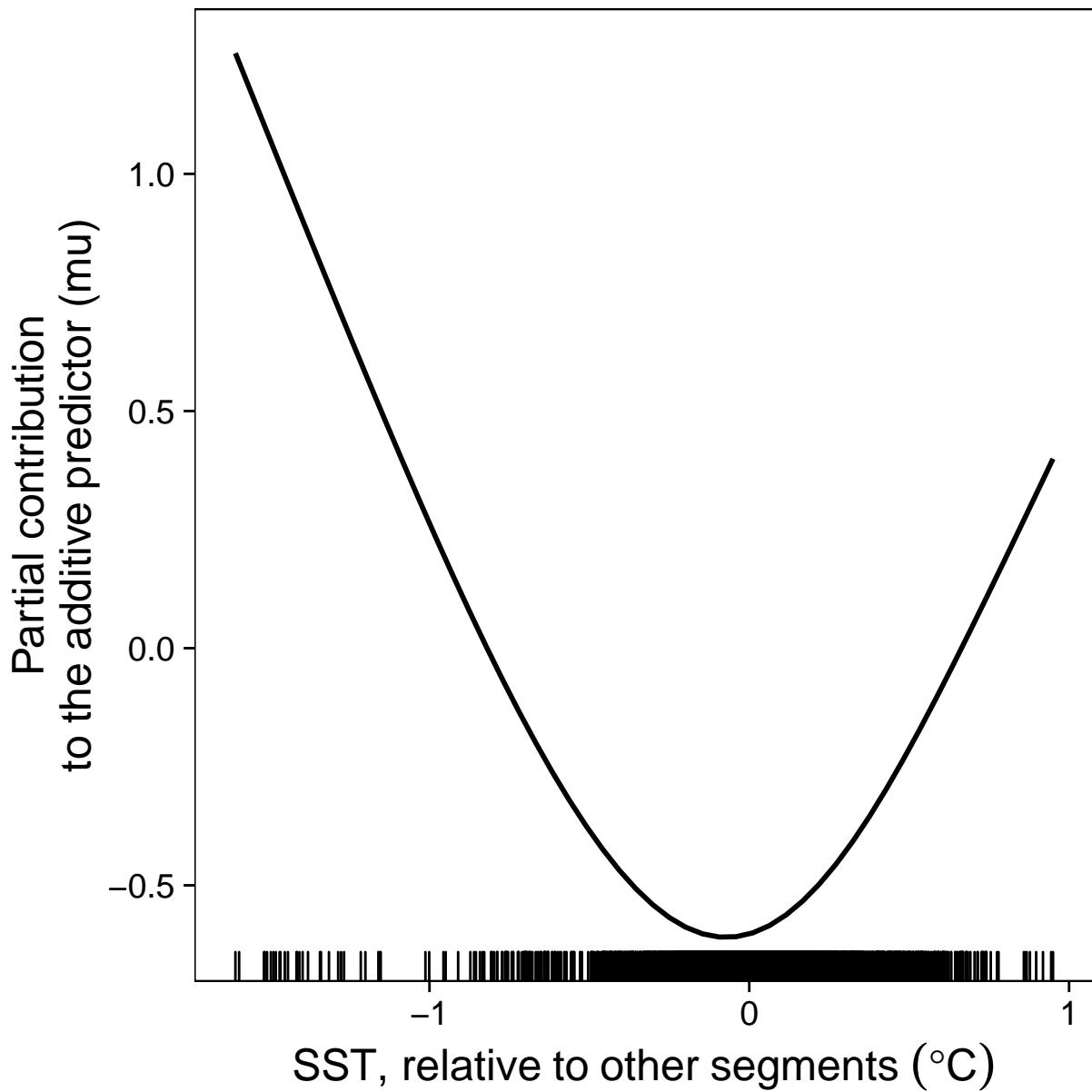


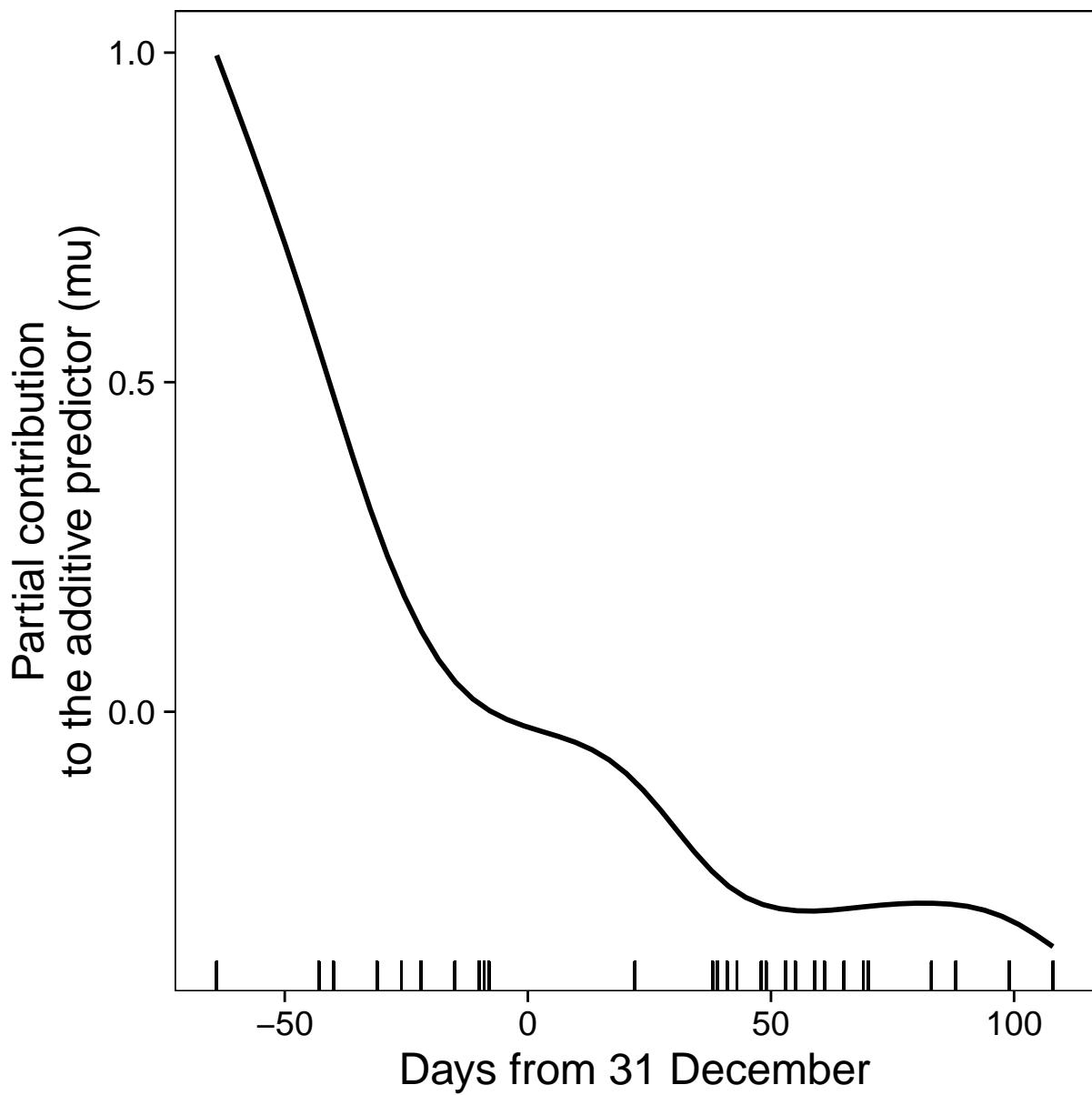


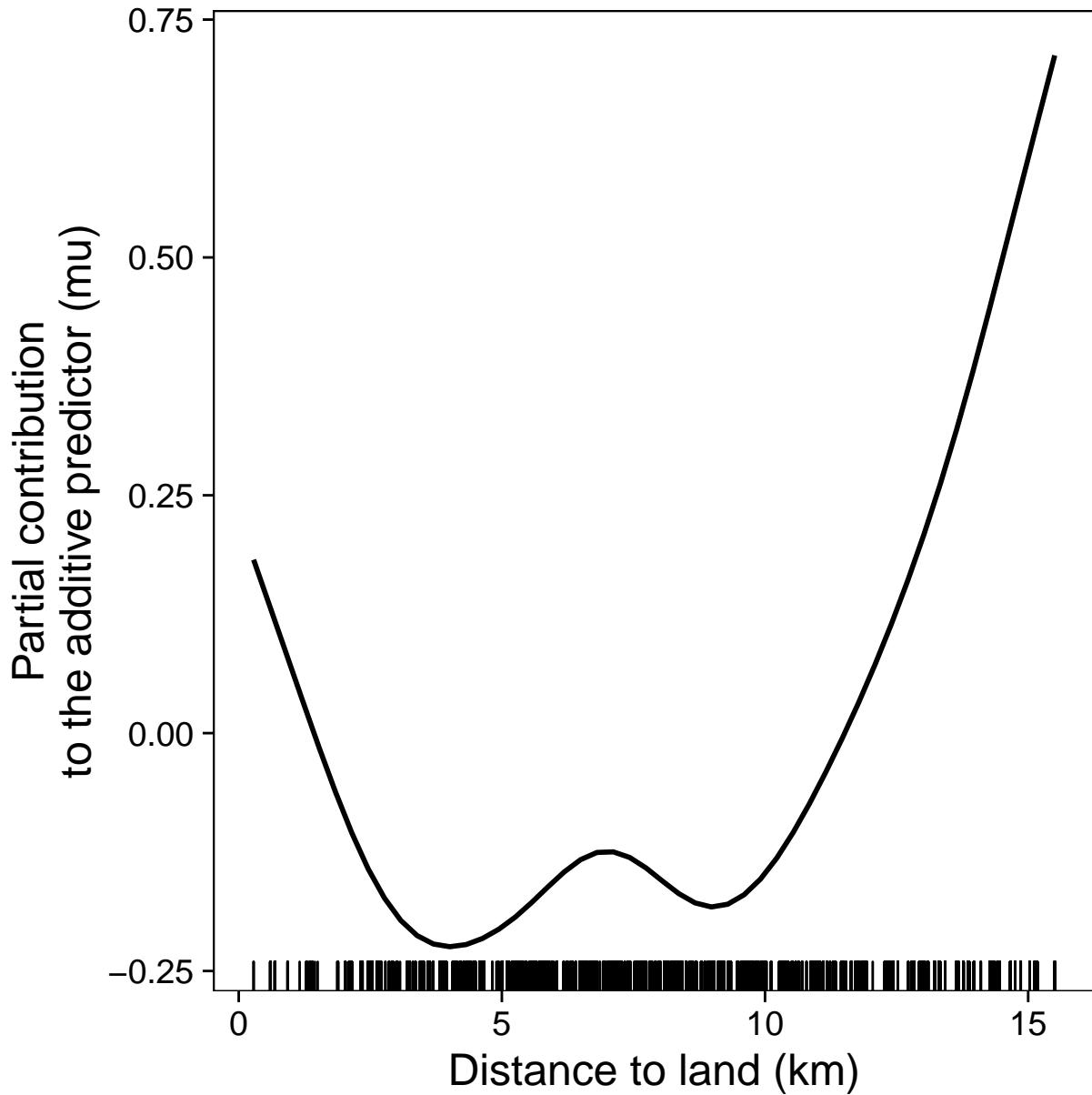


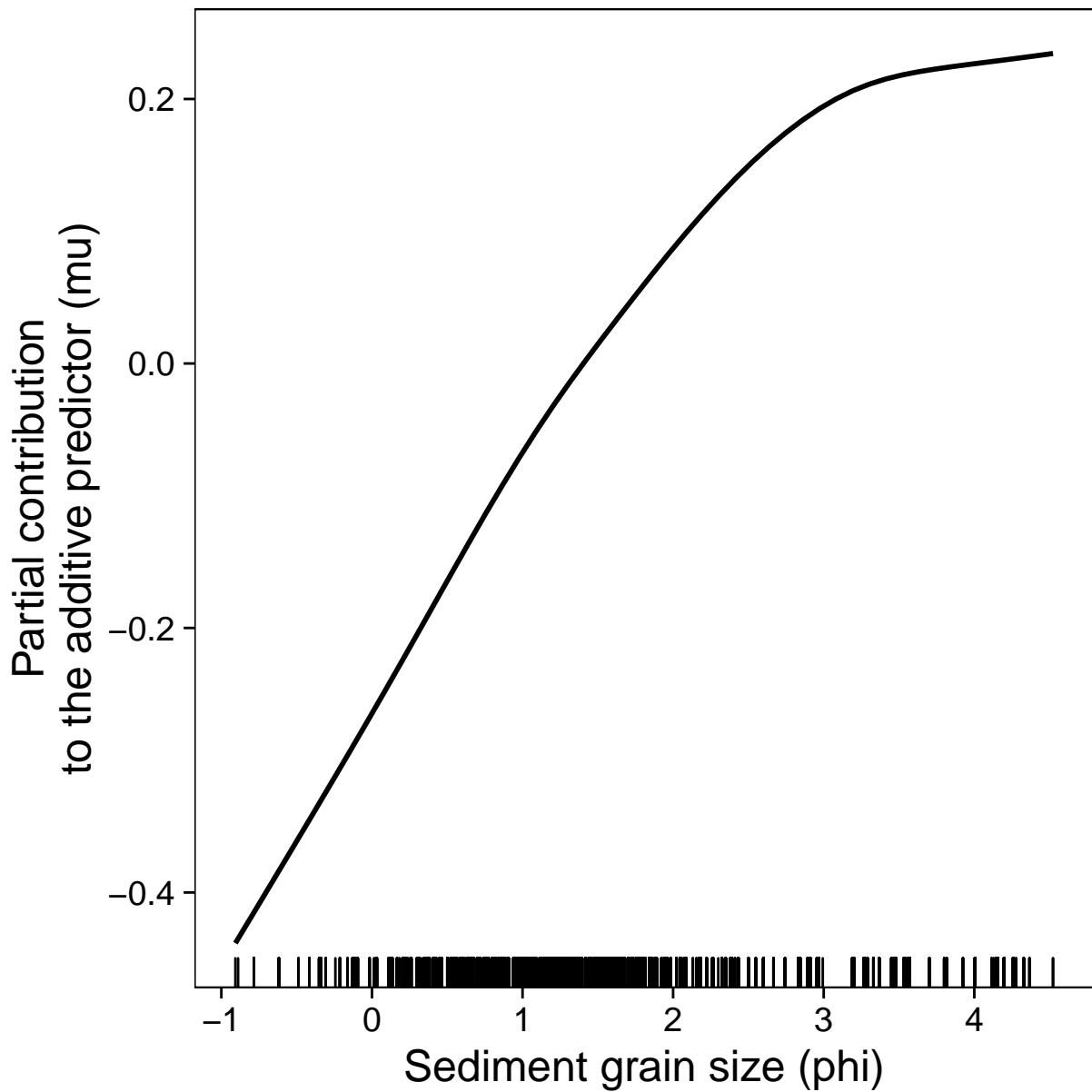
Conditional mean



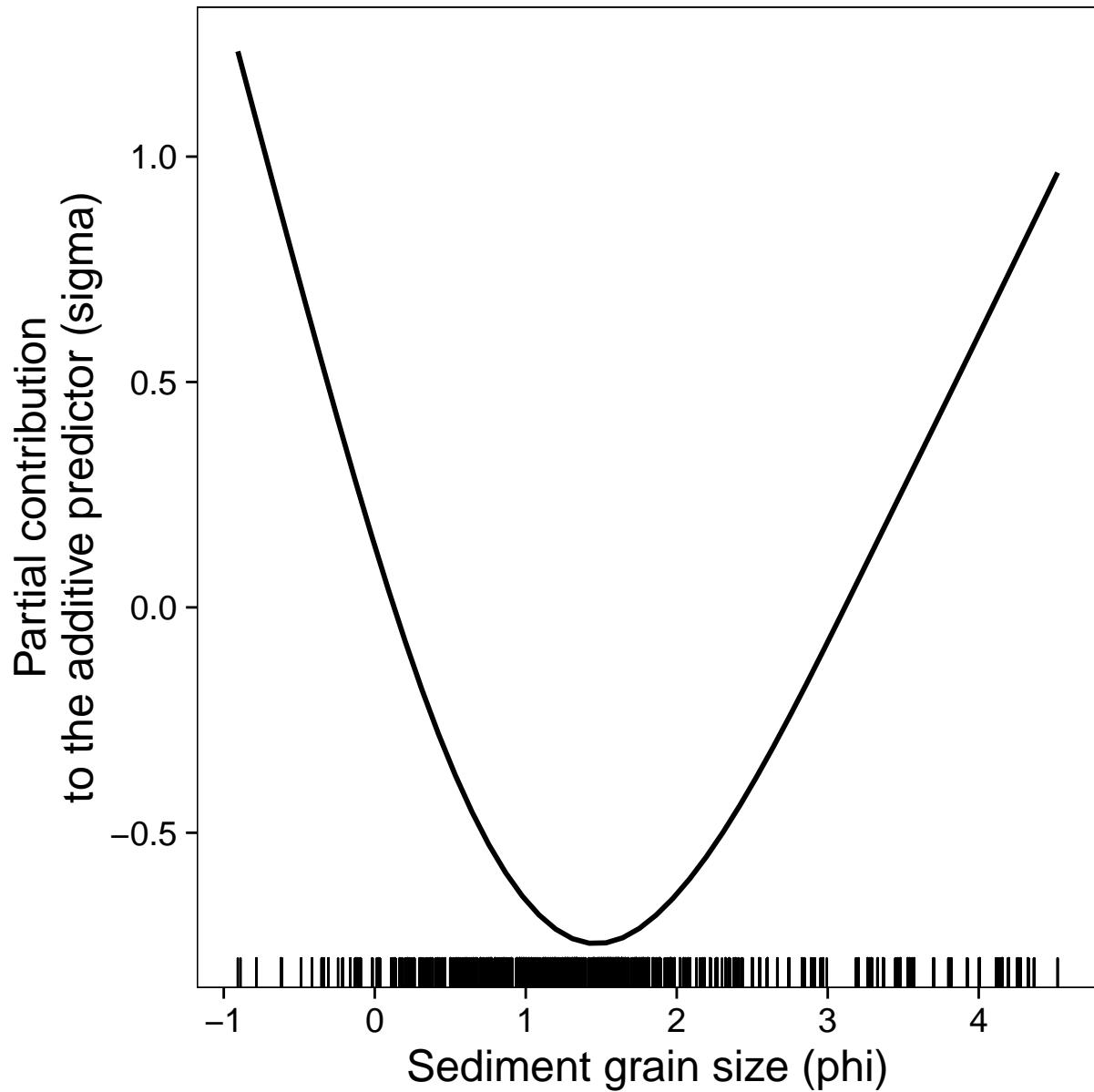


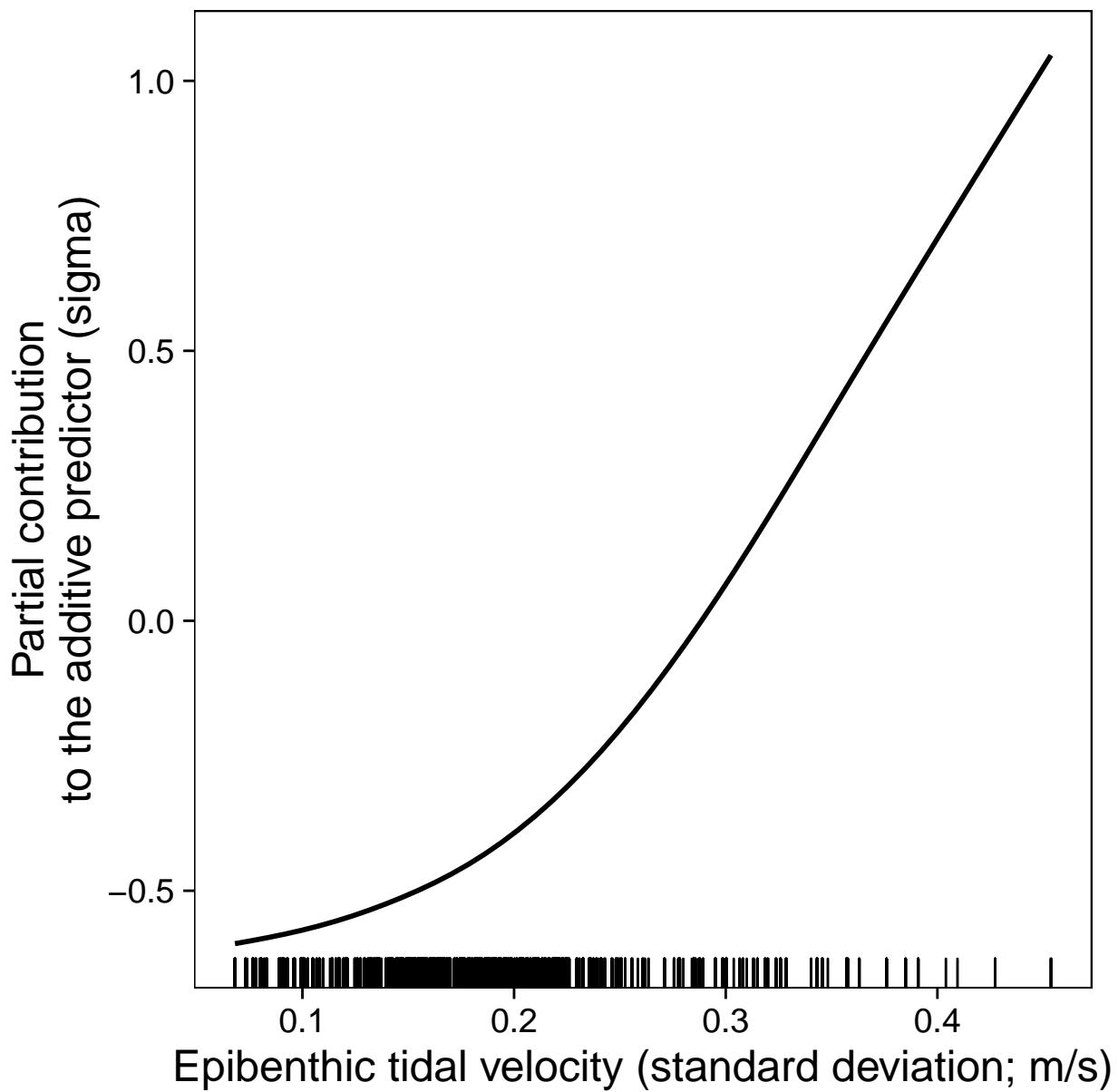


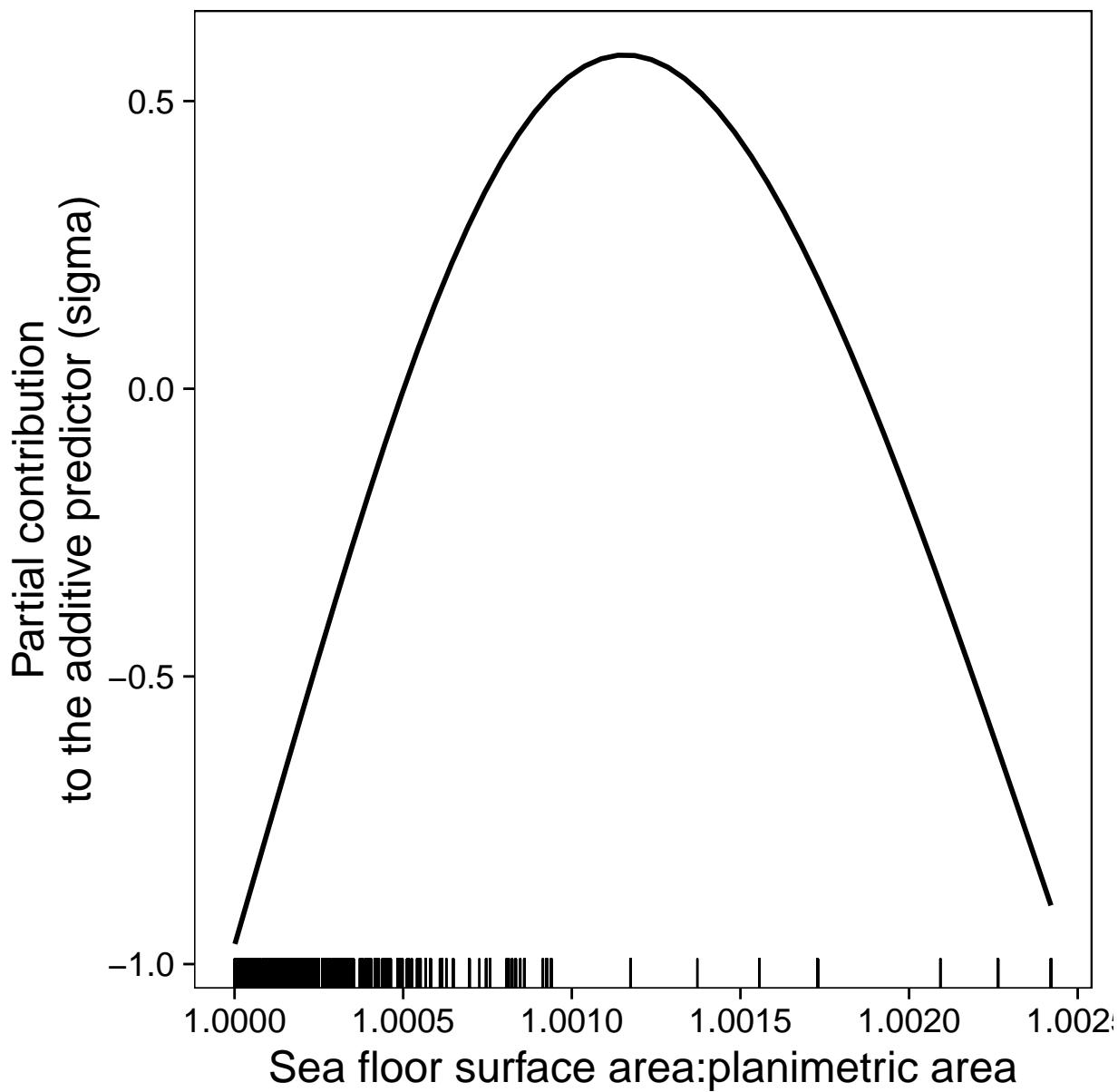


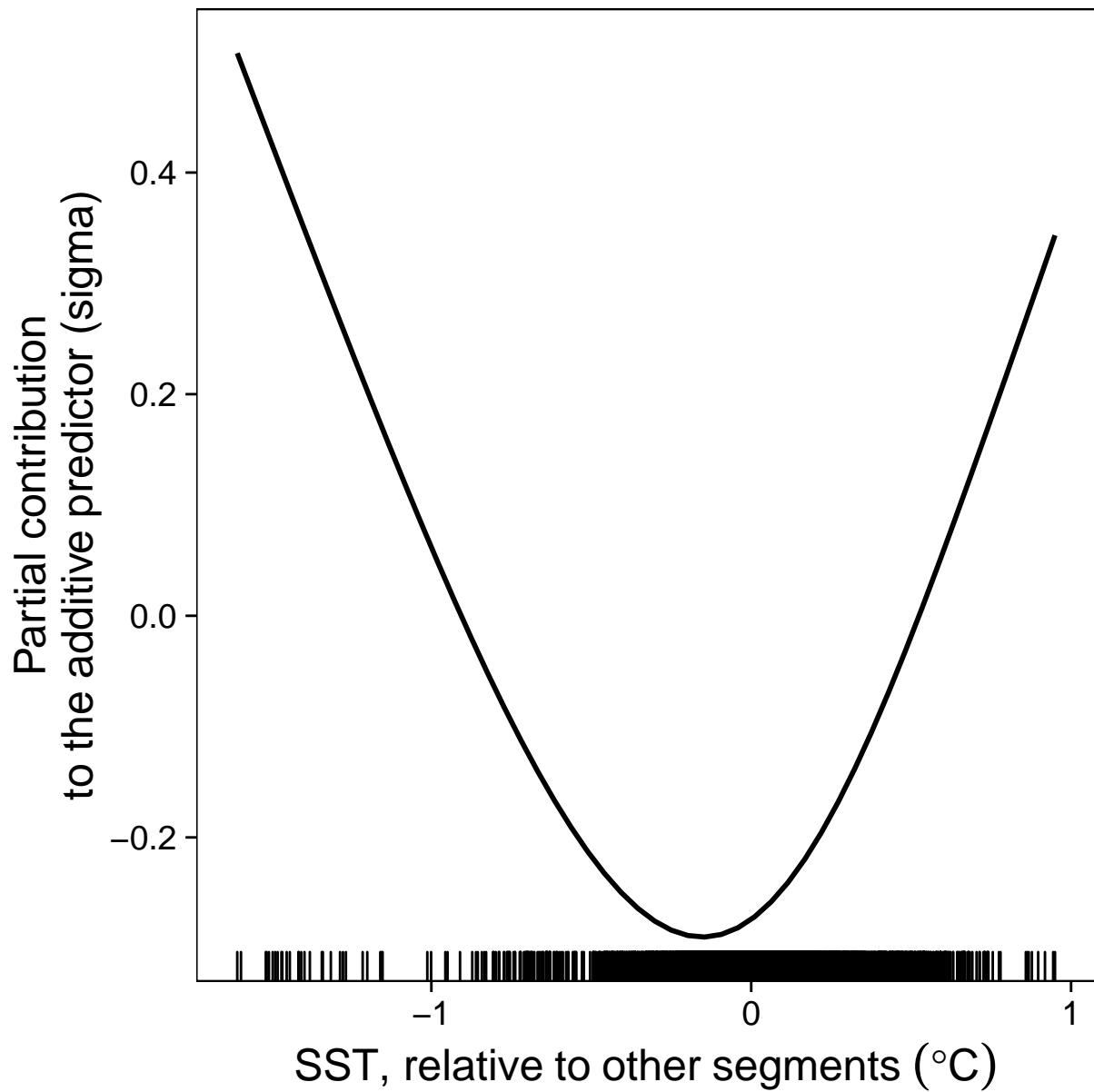


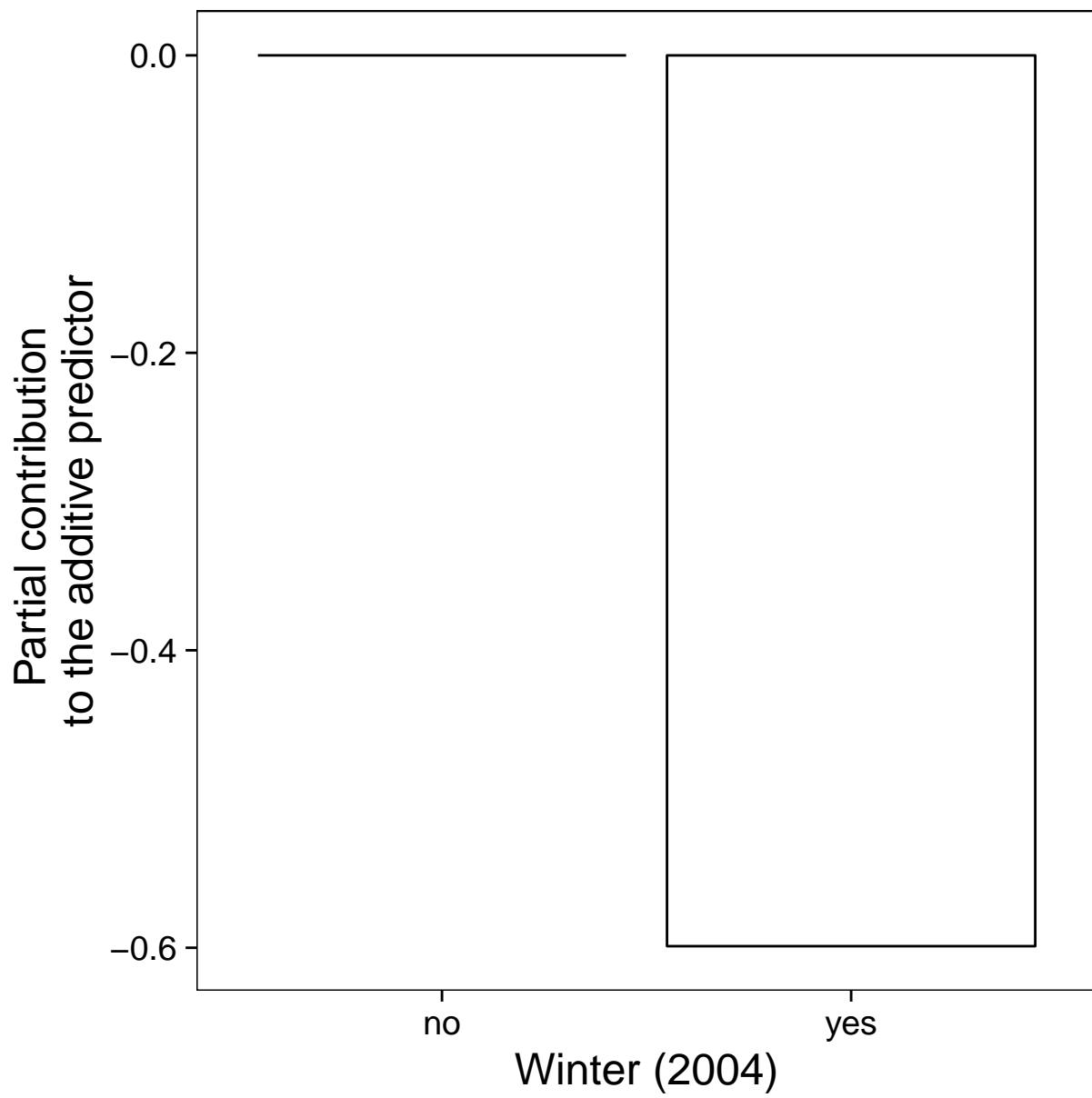
Conditional overdispersion

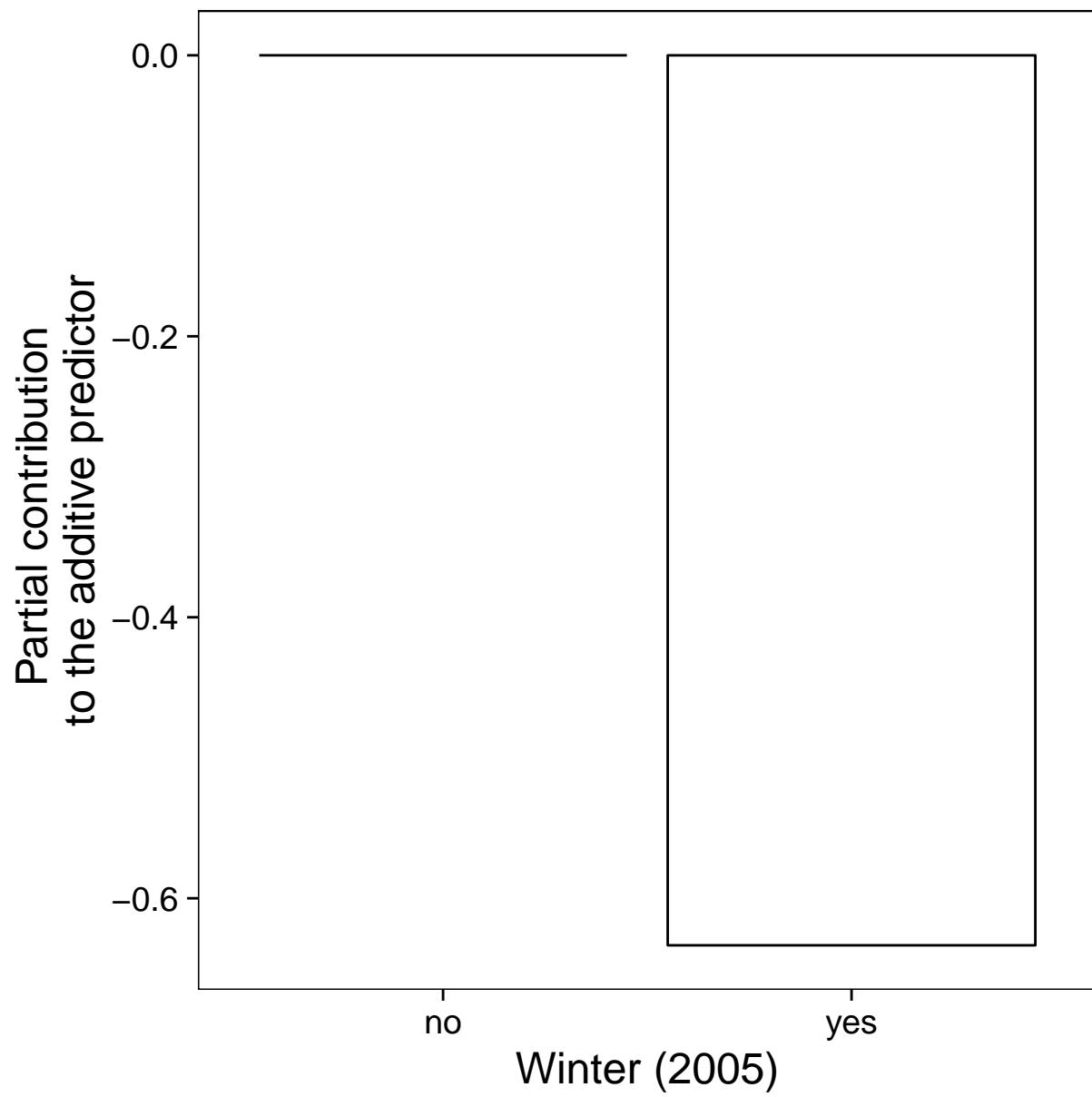








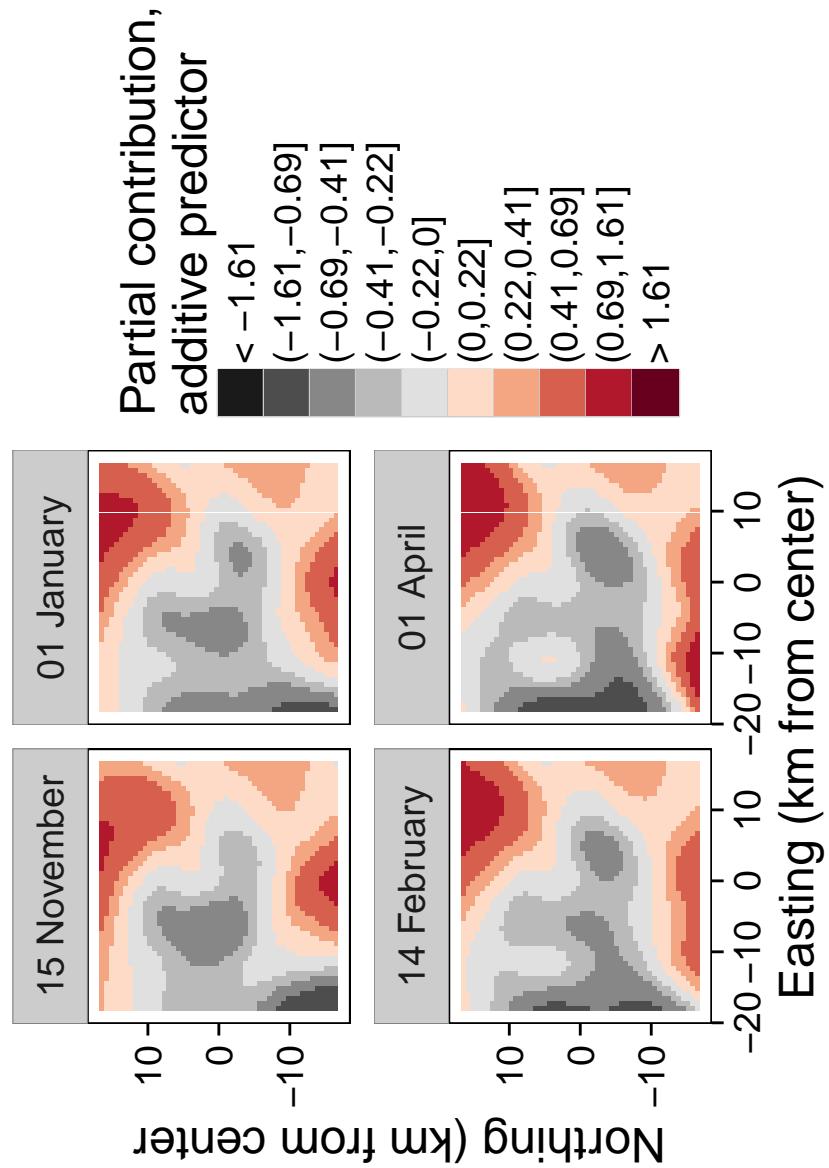


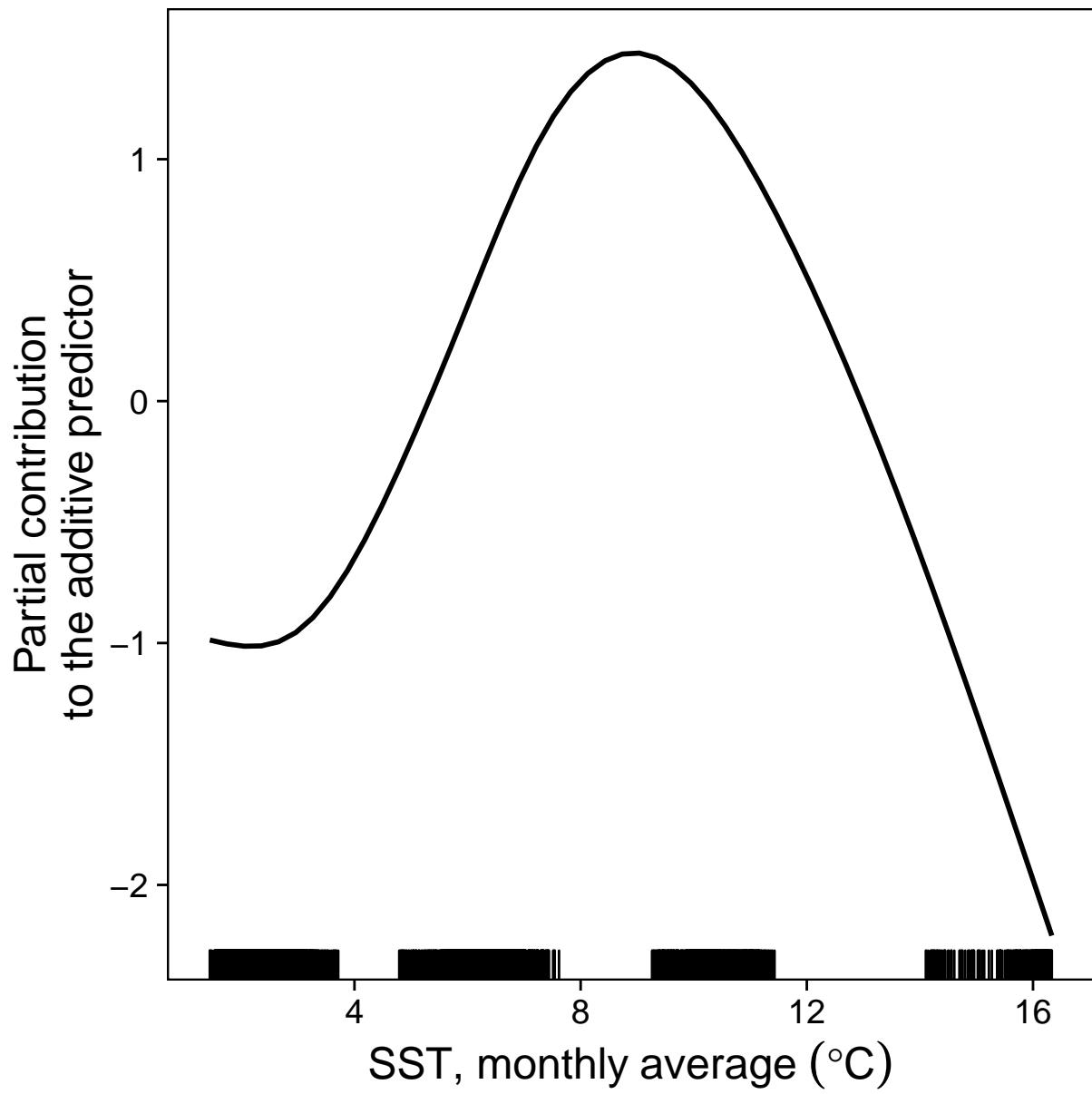


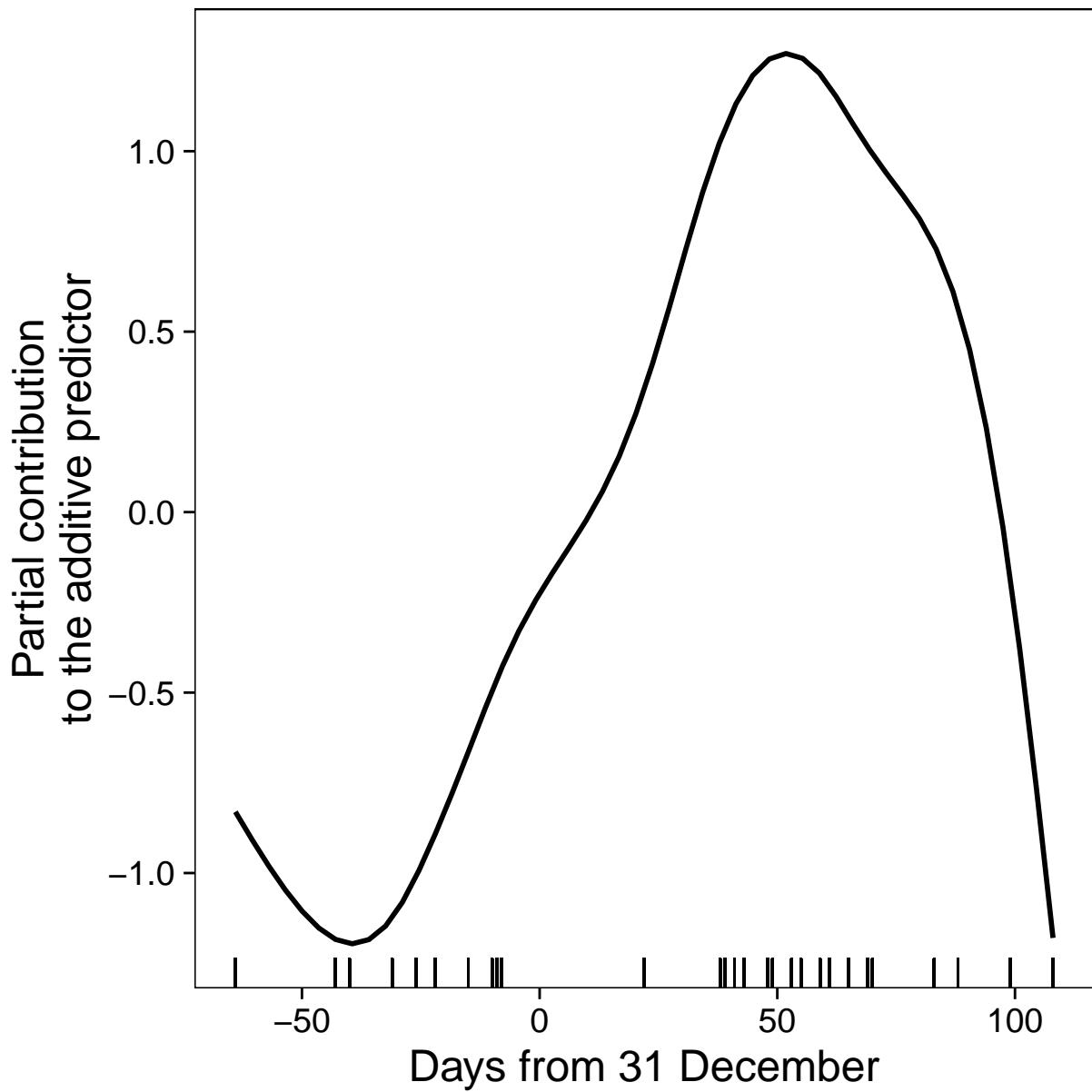
Appendix 7. Long-tailed Duck stable covariate effects

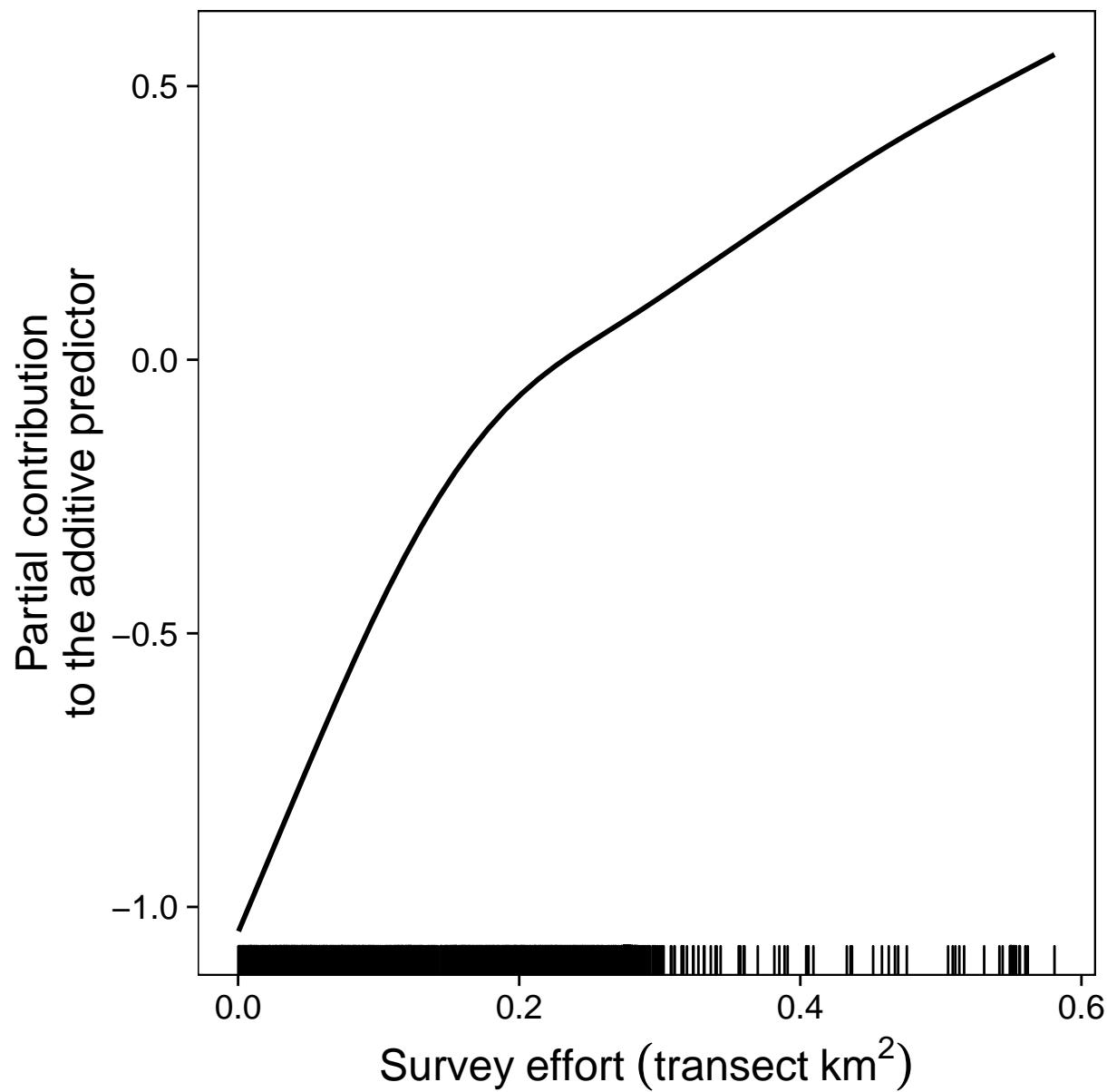
Marginal functional plots of the relationships between covariates (controlling for all other variables; i.e., at their mean values) and the occupancy, conditional mean abundance, and conditional overdispersion of abundance of Long-tailed Duck in Nantucket Sound, Massachusetts, USA. Covariate plots are ordered roughly in descending order of the magnitude of their influence on the additive predictor in each model (or model parameter for count models). Vertical lines along the x -axis (i.e., rug plots) indicate observed covariate values. Covariates (and any abbreviations) are defined in detail in Appendix 2; only effects selected to be stable (see Appendix 1) are depicted.

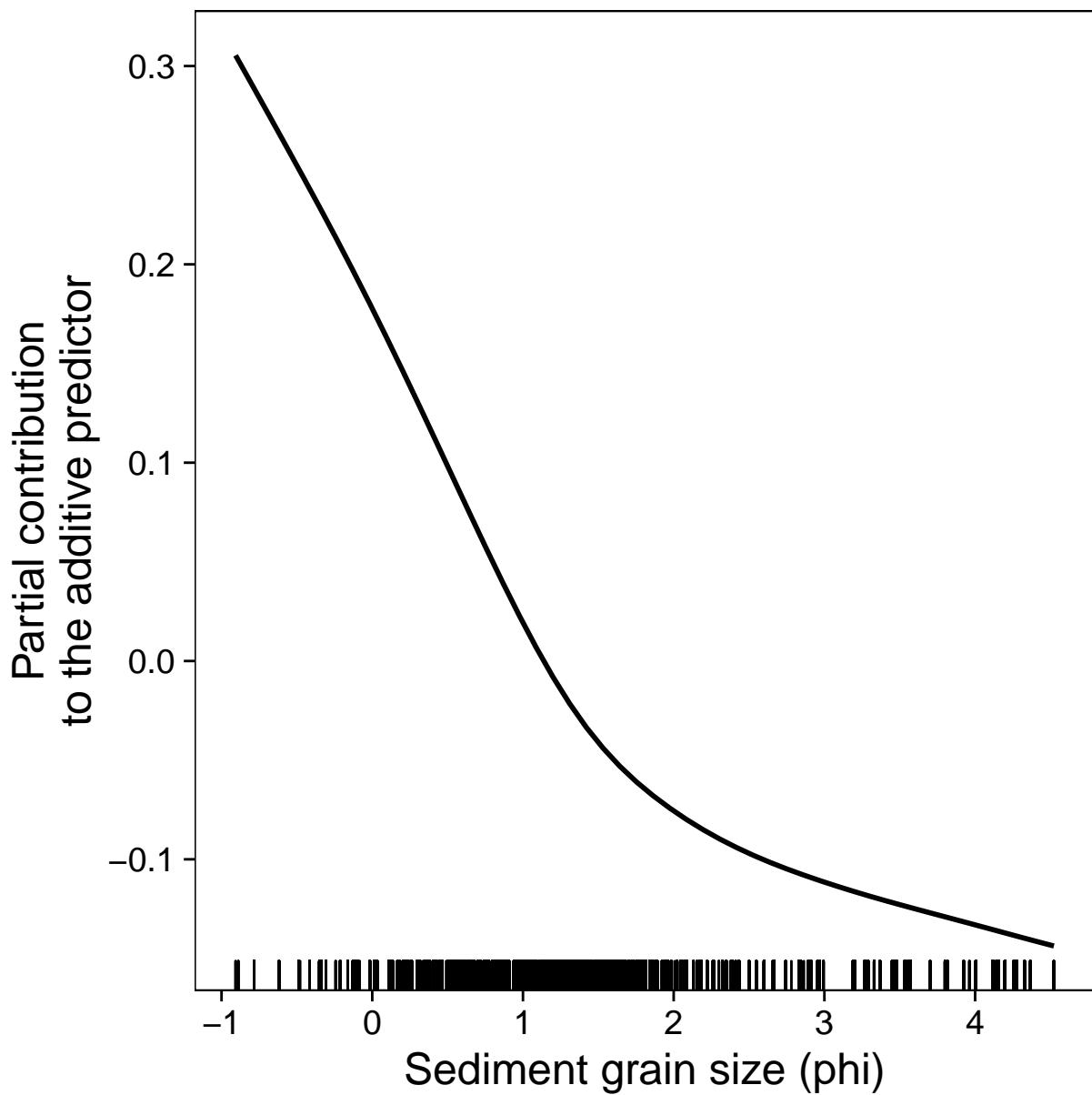
Occupancy

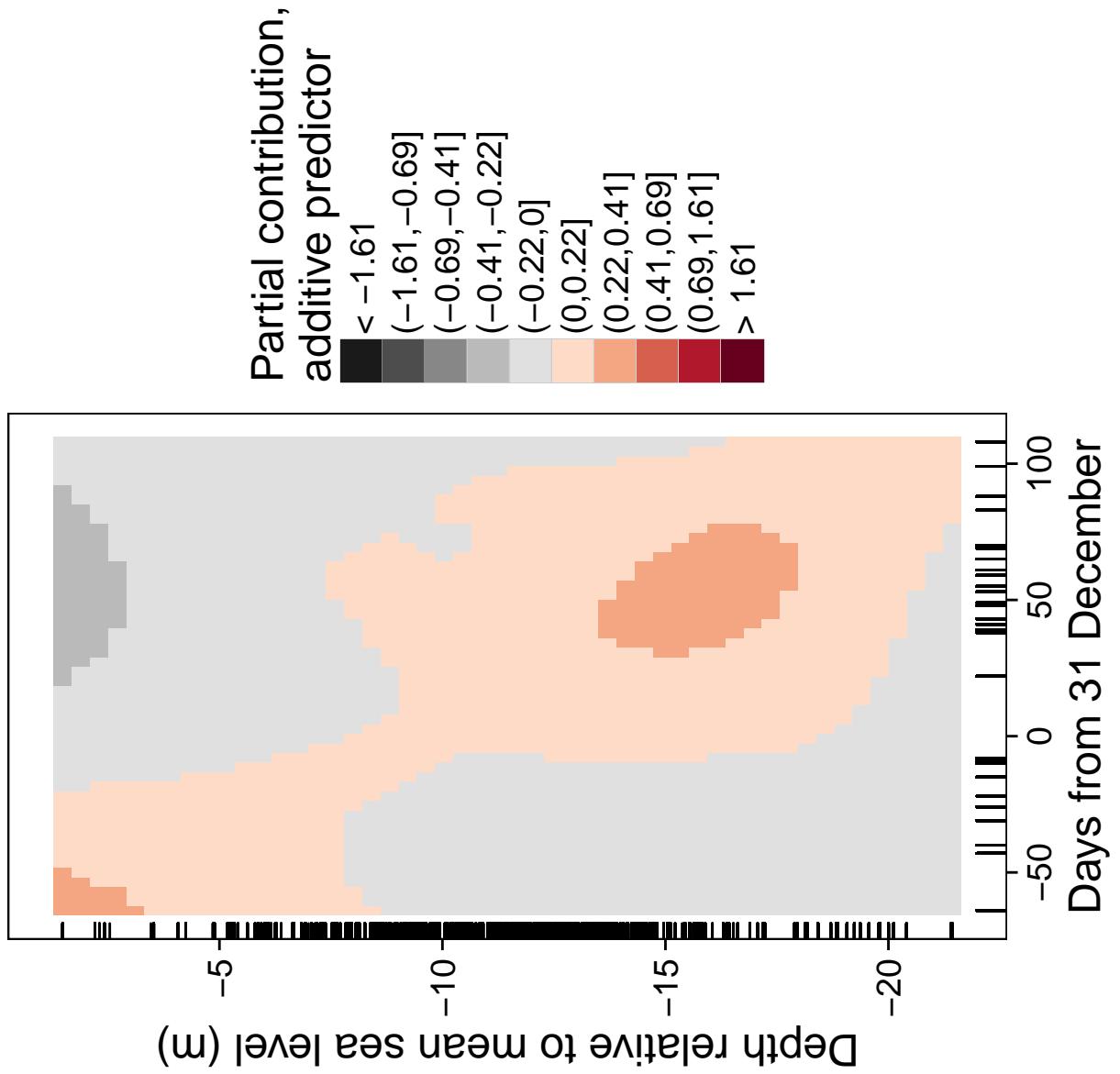


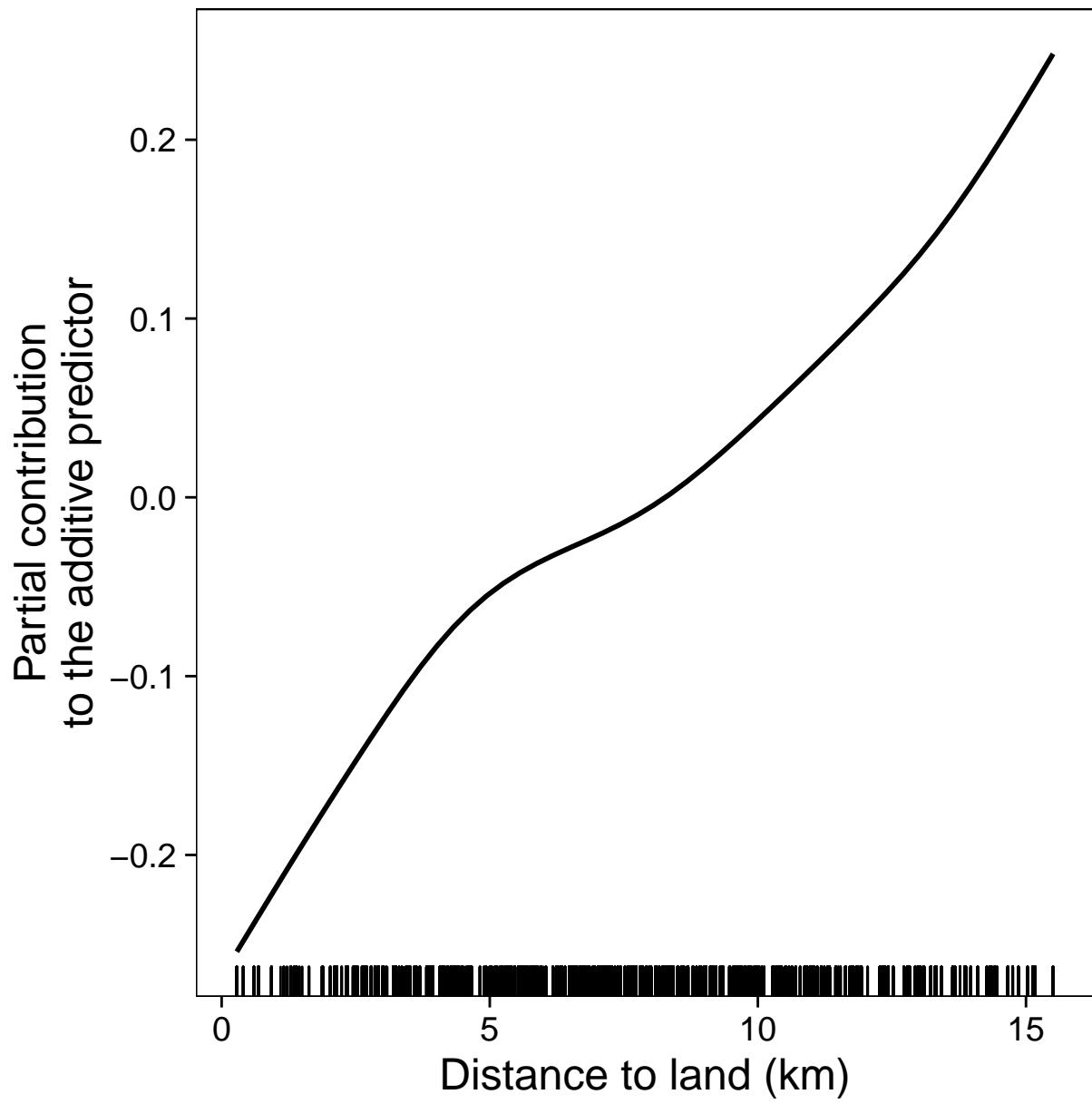


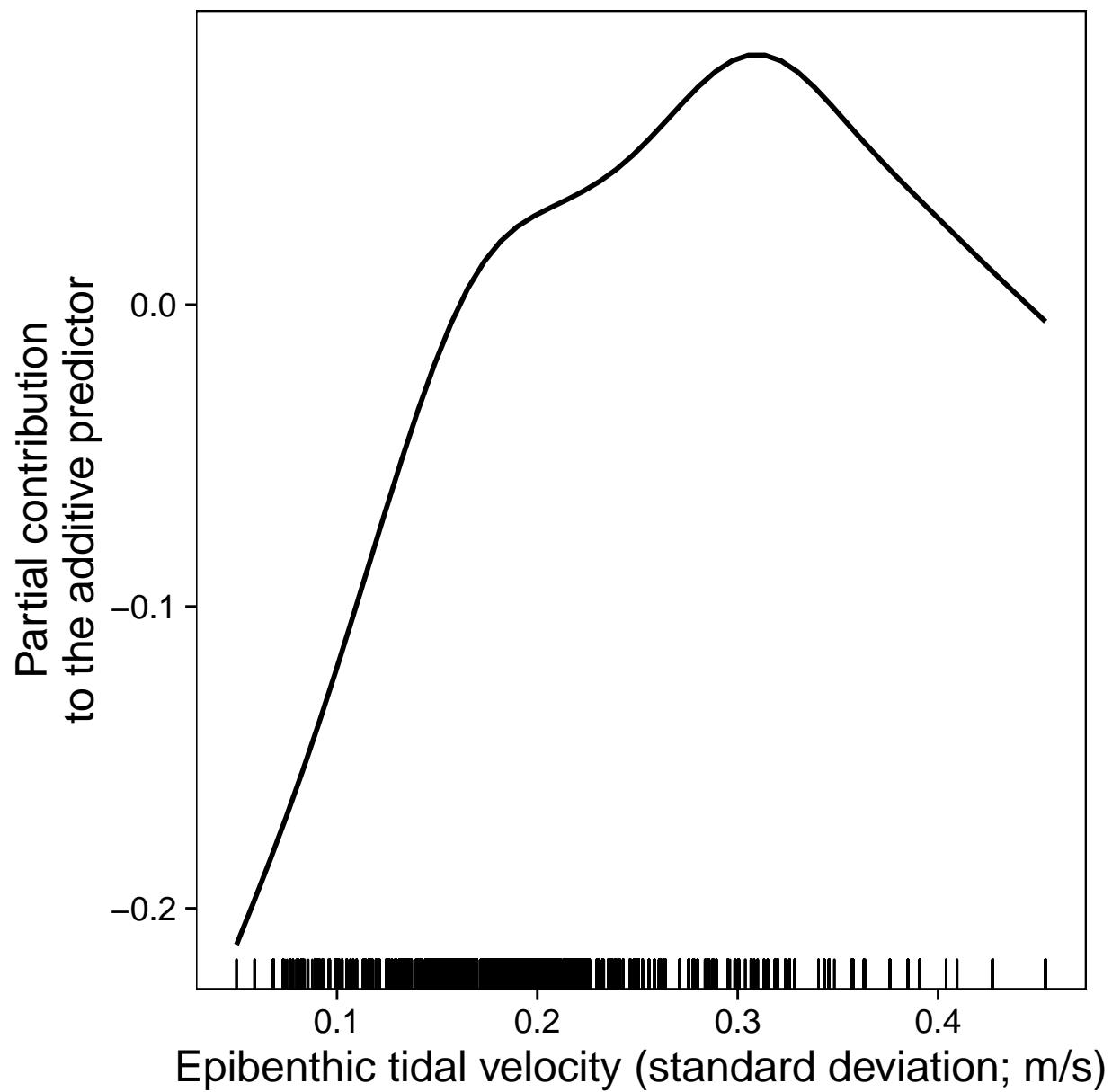


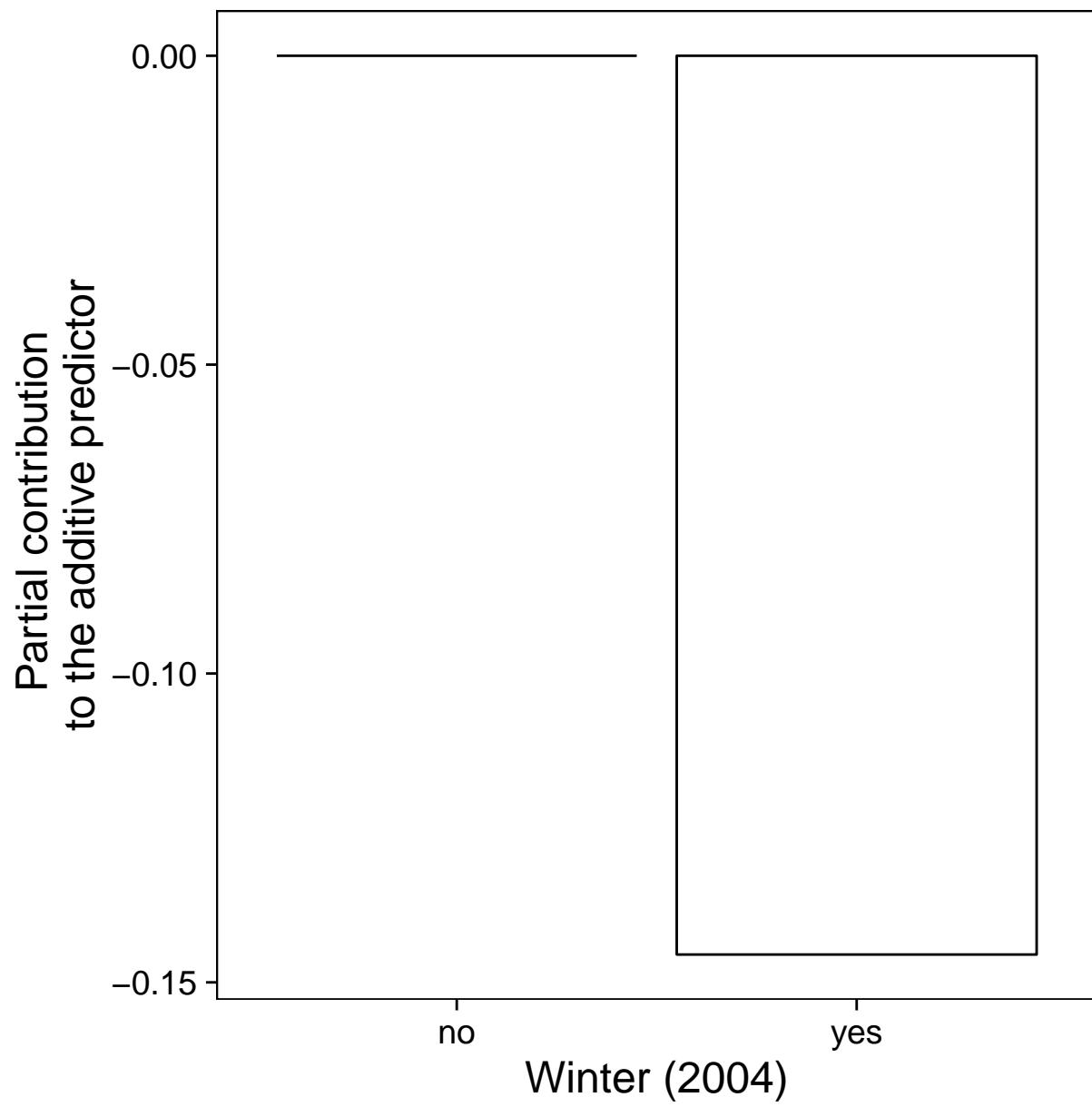




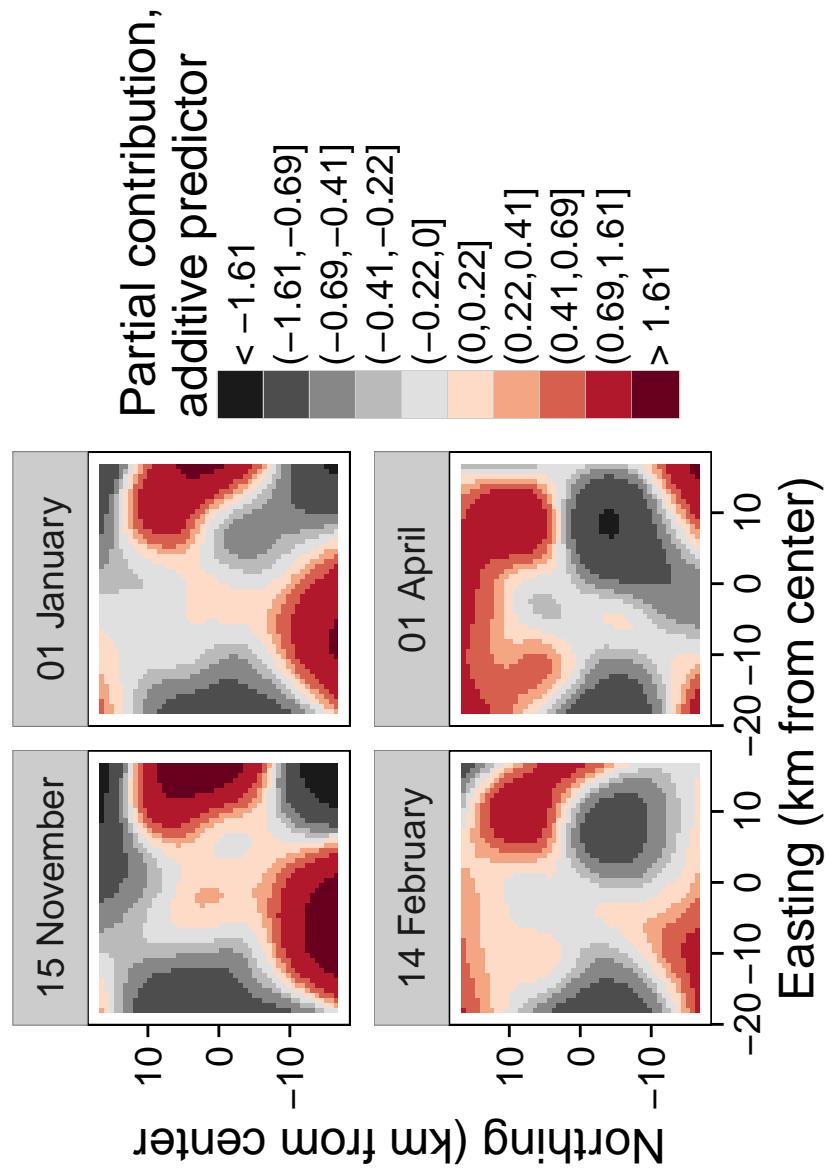


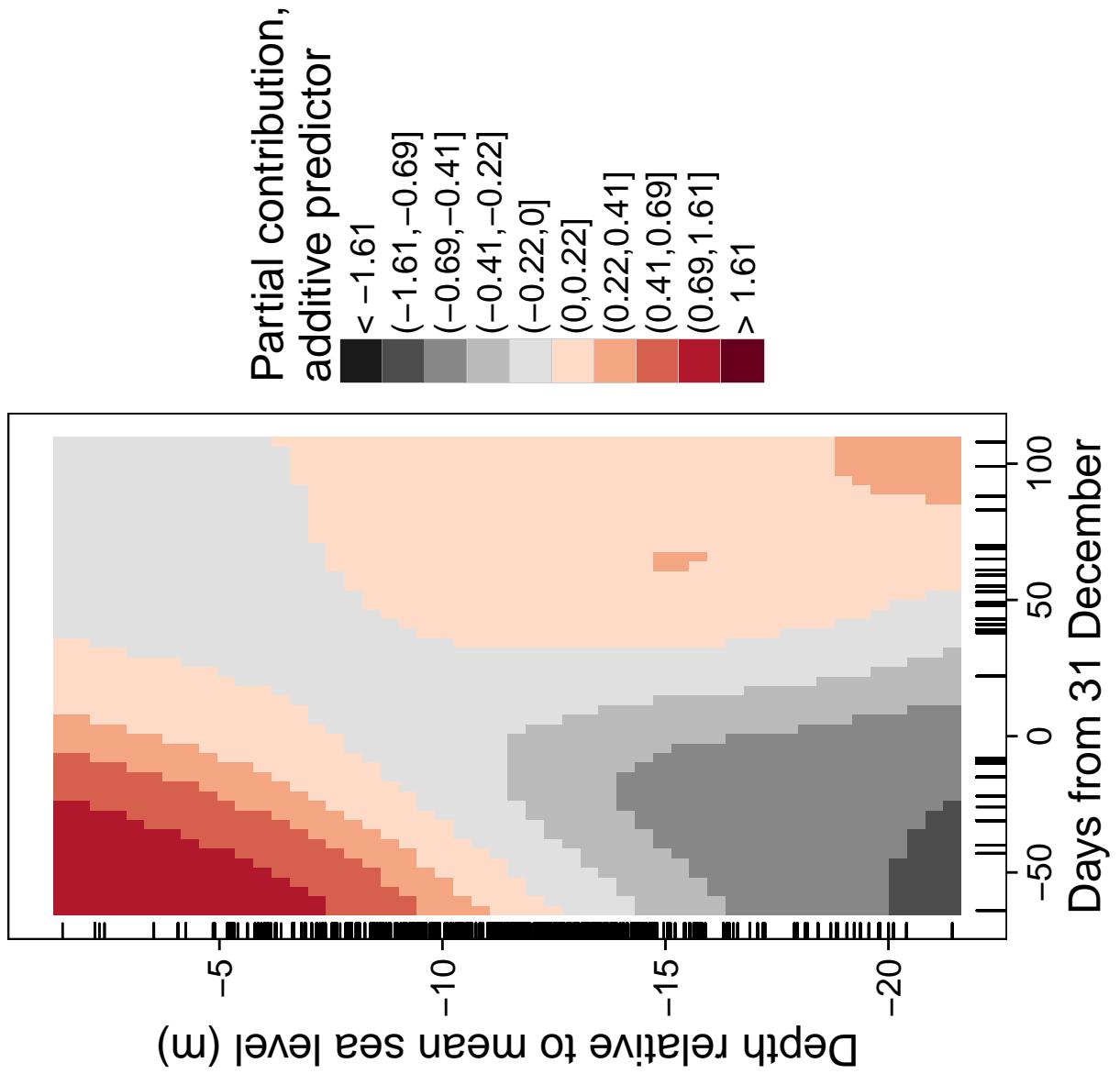


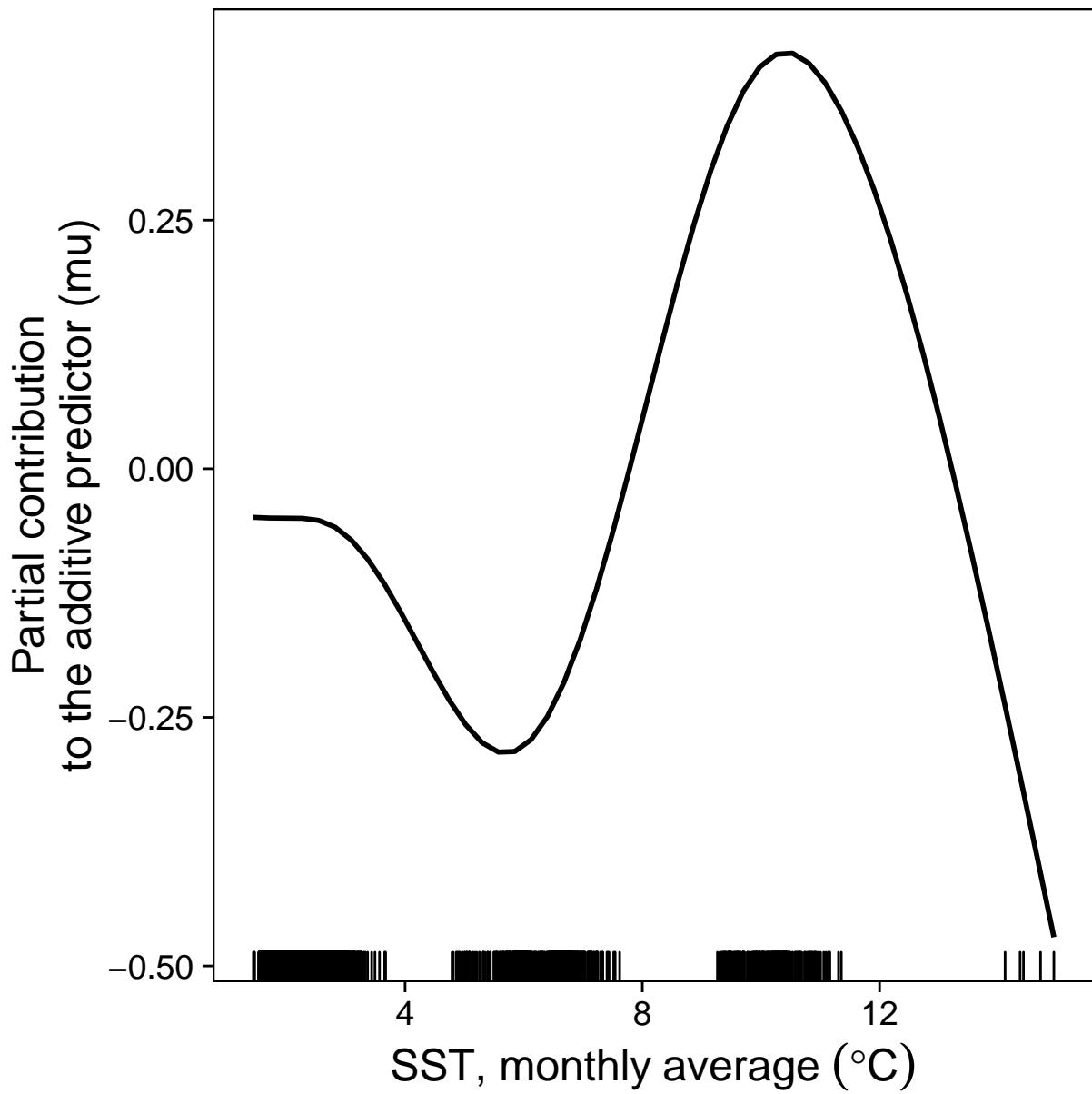




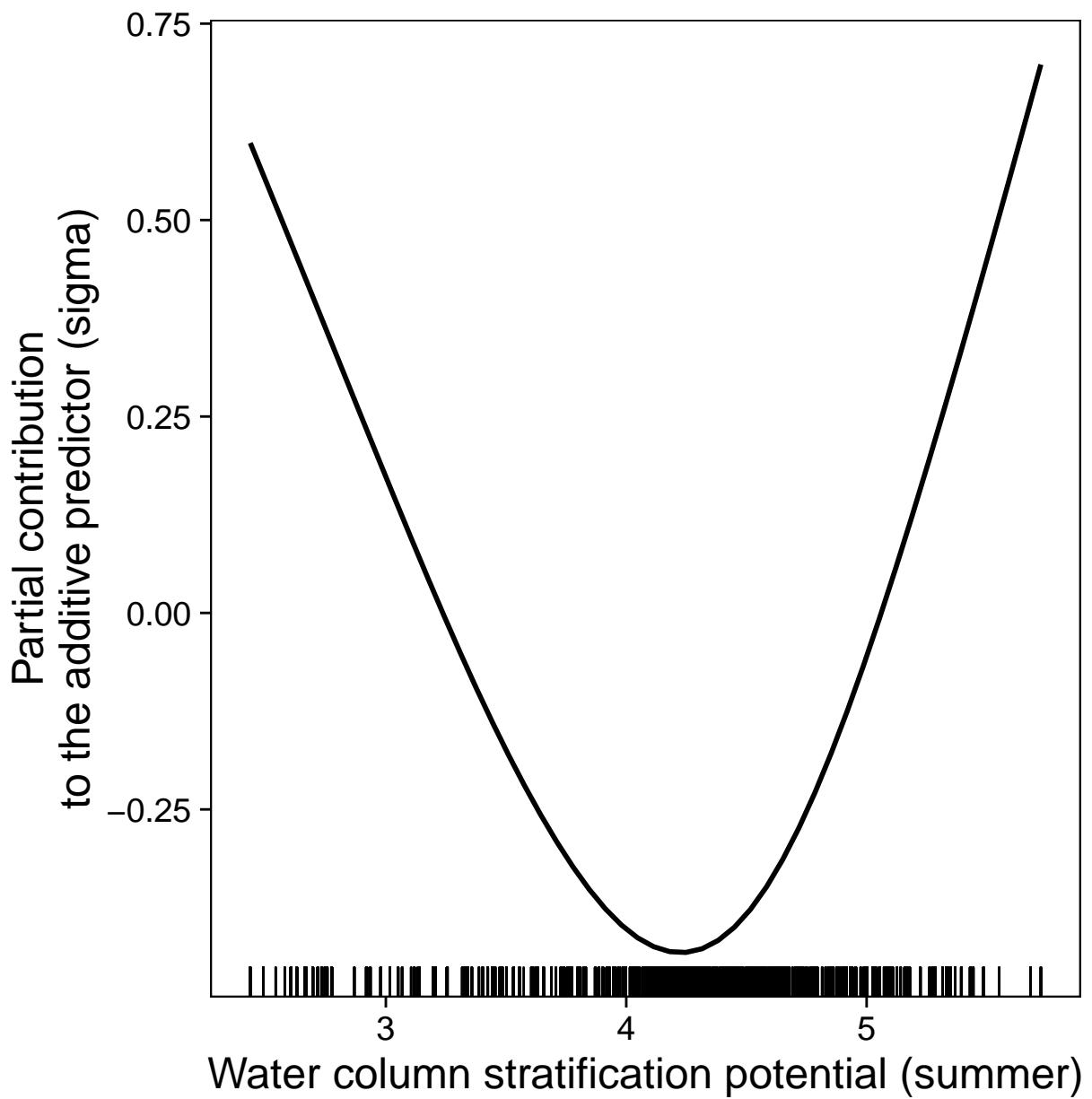
Conditional mean







Conditional overdispersion



Appendix 8. Conditional overdispersion in sea duck abundance

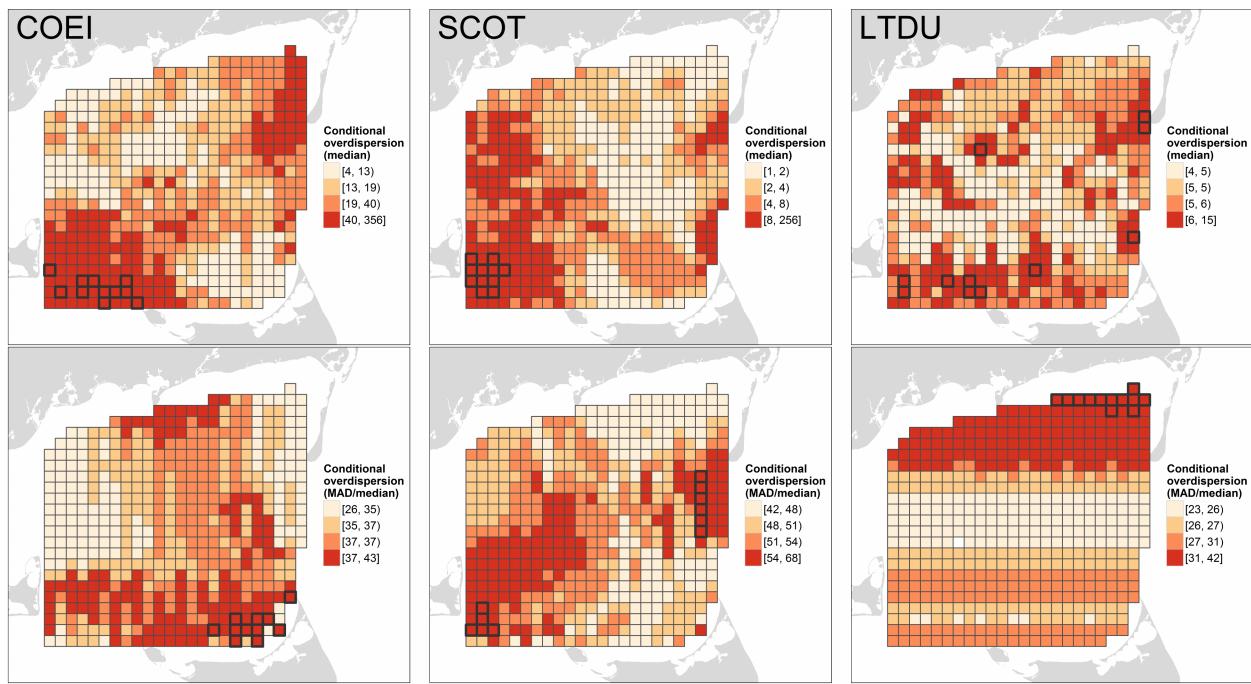


Figure 8.1. Overdispersion in the conditional abundance of Common Eider (COEI), scoter (SCOT), and Long-tailed Duck (LTDU) in Nantucket Sound during three winters, 2003 – 2005. Higher median conditional overdispersion values (top row) indicate increased variance in excess of the mean in the negative binomial model in counts of sea ducks, assuming their presence, in a 1.5 km x ca. 180 m transect in each segment predicted on 10 evenly-spaced dates from 15 November through 1 April in each winter. Spatiotemporal variation in conditional overdispersion (%) (bottom row) is indicated by the median absolute deviation, MAD, relative to the median. Predicted values are categorized based on their quartiles; segments with highest overdispersion or variability (values = 98th percentile) are outlined in black.

Appendix 9. Seasonal animation of predicted scoter occupancy and abundance

To provide an example of the seasonal dynamics that can characterize sea duck occupancy and abundance in Nantucket Sound, we provide an animation of predicted scoter occupancy and overall abundance (scoter per 1.5 km x ca. 180 m) for every other day between 1 November 2005 and 31 March 2006.

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