Example script for VAST for spatio-temporal analysis of multispecies catch-rate data

James Thorson

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Contents

```
## package 'pander' successfully unpacked and MD5 sums checked
##
## The downloaded binary packages are in
##  C:\Users\James.Thorson\AppData\Local\Temp\RtmpWeNoDp\downloaded_packages
```

1 Overview

This tutorial will walk through a simple example of how to use `VAST` for estimating abundance indices, distribution shifts, and range expansion using (1) biomass/count samples for a single species, (2) biomass/count samples for multiple ages/sizes of a single species, or (3) biomass/count samples for multiple species.

2 Getting started

To install TMB on a windows machine, we need to first install Rtools. During the installation, please select the option to have Rtools included in your system path. On other operating systems, it is not necessary to install Rtools. We then install `VAST`.

```
devtools::install_github("james-thorson/VAST")
```

We also install `FishData`, which is used to download data for our example

```
devtools::install_github("james-thorson/FishData")
```

Next load libraries.

```
library(TMB)               # Can instead load library(TMBdebug)
```

```
## Warning: package 'TMB' was built under R version
## 3.3.2
```

```
library(VAST)
```

2.1 Further information

If you have further questions after reading this tutorial, please explore the GitHub repo mainpage, wiki, and glossary. Also please explore the R help files, e.g., e.g., `?Data_Fn` for explanation of data inputs, or `?Param_Fn` for explanation of parameters.

2.2 Related tools

Related tools for spatio-temporal fisheries analysis are currently housed at www.FishStats.org. These include SpatialDeltaGLMM, a single-species antecedent of VAST, and www.FishViz.org, a tool for visualizing single-species results using worldwide. `VAST` and `SpatialDeltaGLMM` both use continuous integration to confirm that they give identical estimates when applied to single-species data.

2.3 How to cite SpatialDeltaGLMM

`VAST` has involved many publications for developing individual features. If using `VAST`, please read and cite:

```
citation("VAST")
```

```
##
## Please cite 2016 (ICES J. Mar. Sci. J.
## Cons.) if using the package; 2016 (Glob.
## Ecol. Biogeogr) if exploring factor
## decomposition of spatio-temporal variation;
## 2015 (ICES J. Mar. Sci. J. Cons.) if
## calculating an index of abundance; 2016
## (Methods Ecol. Evol.) if using the
## center-of-gravity metric; 2016 (Fish. Res.)
## if using the bias-correction feature; 2016
## (Proc R Soc B) if using the
## effective-area-occupied metric.
##
##   Thorson, J.T., and Barnett, L.A.K. In
##   press. Comparing estimates of abundance
##   trends and distribution shifts using
##   single- and multispecies models of fishes
##   and biogenic habitat. ICES J. Mar. Sci. J.
##   Cons
##
##   Thorson, J.T., Ianelli, J.N., Larsen, E.,
##   Ries, L., Scheuerell, M.D., Szuwalski, C.,
##   and Zipkin, E. 2016. Joint dynamic species
##   distribution models: a tool for community
##   ordination and spatiotemporal monitoring.
##   Glob. Ecol. Biogeogr. 25(9): 1144-1158.
##   doi:10.1111/geb.12464. url:
##   http://onlinelibrary.wiley.com/doi/10.1111/geb.12464/abstract
##
##   Thorson, J.T., Shelton, A.O., Ward, E.J.,
##   Skaug, H.J., 2015. Geostatistical
##   delta-generalized linear mixed models
##   improve precision for estimated abundance
##   indices for West Coast groundfishes. ICES
##   J. Mar. Sci. J. Cons. 72(5), 1297-1310.
##   doi:10.1093/icesjms/fsu243. URL:
##   http://icesjms.oxfordjournals.org/content/72/5/1297
##
##   Thorson, J.T., and Kristensen, K. 2016.
##   Implementing a generic method for bias
```

```
##   correction in statistical models using
##   random effects, with spatial and
##   population dynamics examples. Fish. Res.
##   175: 66-74.
##   doi:10.1016/j.fishres.2015.11.016. url:
##   http://www.sciencedirect.com/science/article/pii/S0165783615301399
##
##   Thorson, J.T., Pinsky, M.L., Ward, E.J.,
##   2016. Model-based inference for estimating
##   shifts in species distribution, area
##   occupied, and center of gravity. Methods
##   Ecol. Evol. 7(8), 990-1008.
##   doi:10.1111/2041-210X.12567.  URL:
##   http://onlinelibrary.wiley.com/doi/10.1111/2041-210X.12567/full
##
##   Thorson, J.T., Rindorf, A., Gao, J.,
##   Hanselman, D.H., and Winker, H. 2016.
##   Density-dependent changes in effective
##   area occupied for sea-bottom-associated
##   marine fishes. Proc R Soc B 283(1840):
##   20161853. doi:10.1098/rspb.2016.1853. URL:
##   http://rspb.royalsocietypublishing.org/content/283/1840/20161853.
```

and also browse the GitHub list of papers.

3 Settings

We use latest version for CPP code

```
Version = "VAST_v2_0_0"
```

3.1 Spatial settings

The following settings define the spatial resolution for the model, and whether to use a grid or mesh approximation

```
Method = c("Grid", "Mesh", "Spherical_mesh")[2]
grid_size_km = 50
n_x = c(50, 100, 250, 500, 1000, 2000)[1] # Number of stations
Kmeans_Config = list( "randomseed"=1, "nstart"=100, "iter.max"=1e3 )
```

3.2 Model settings

The following settings define whether to include spatial and spatio-temporal variation, the rank of this covariance among species, whether its autocorrelated, and whether there's overdispersion

```
FieldConfig = c(Omega1 = 3, Epsilon1 = 3, Omega2 = 3,
    Epsilon2 = 3)
RhoConfig = c(Beta1 = 0, Beta2 = 0, Epsilon1 = 0, Epsilon2 = 0)
OverdispersionConfig = c(Vessel = 0, VesselYear = 0)
ObsModel = c(2, 0)
```

We also decide on which post-hoc calculations to include in the output

```
Options = c(SD_site_density = 0, SD_site_logdensity = 0,
    Calculate_Range = 1, Calculate_evenness = 0, Calculate_effective_area = 1,
    Calculate_Cov_SE = 0, Calculate_Synchrony = 0,
    Calculate_Coherence = 0)
```

3.3 Stratification for results

We also define any potential stratification of results, and settings specific to any case-study data set

```
strata.limits <- data.frame(STRATA = "All_areas")
```

3.4 Derived objects

In this case, we'll use publicly available data for three groundfishes in the Eastern Bering Sea, so we set `Region` and `Species_set` accordingly. `Region` is used to define both the database for downloading data, as well as the region for extrapolation density, while `Species_set` is only used when downloading data.

```
Region = "Eastern_Bering_Sea"
Species_set = c("Atheresthes stomias","Gadus chalcogrammus","Hippoglossoides elassodon")
```

3.5 Save settings

We then set the location for saving files.

```
DateFile = paste0(getwd(),'/VAST_output/')
  dir.create(DateFile)
```

I also like to save all settings for later reference, although this is not necessary.

```
Record = list(Version = Version, Method = Method, grid_size_km = grid_size_km,
    n_x = n_x, FieldConfig = FieldConfig, RhoConfig = RhoConfig,
    OverdispersionConfig = OverdispersionConfig, ObsModel = ObsModel,
    Kmeans_Config = Kmeans_Config, Region = Region,
    Species_set = Species_set, strata.limits = strata.limits)
save(Record, file = file.path(DateFile, "Record.RData"))
capture.output(Record, file = paste0(DateFile, "Record.txt"))
```

4 Prepare the data

4.1 Data-frame for catch-rate data

We then download data for three species using `FishData`.

```
DF = FishData::download_catch_rates(survey = "Eastern_Bering_Sea",
    species_set = Species_set)
Data_Geostat = data.frame(spp = DF[, "Sci"], Year = DF[,
    "Year"], Catch_KG = DF[, "Wt"], AreaSwept_km2 = 0.01,
    Vessel = 0, Lat = DF[, "Lat"], Lon = DF[, "Long"])
```

The data is formatted as shown here, with head…

spp	Year	Catch_KG	AreaSwept_km2	Vessel	Lat	Lon
Atheresthes_stomias	1982	6.98	0.01	0	55	-167
Atheresthes_stomias	1982	4.37	0.01	0	55	-166
Atheresthes_stomias	1982	12.6	0.01	0	55	-166
Atheresthes_stomias	1982	4.28	0.01	0	55	-165
Atheresthes_stomias	1982	0	0.01	0	55	-165
Atheresthes_stomias	1982	10.3	0.01	0	55.3	-167

… and tail

Table 2: Table continues below

	spp	Year	Catch_KG	AreaSwept_km2	Vessel
38878	Hippoglossoides_elassodon	2016	1.15	0.01	0
38879	Hippoglossoides_elassodon	2016	0	0.01	0
38880	Hippoglossoides_elassodon	2016	0	0.01	0
38881	Hippoglossoides_elassodon	2016	0	0.01	0
38882	Hippoglossoides_elassodon	2016	0	0.01	0
38883	Hippoglossoides_elassodon	2016	28	0.01	0

	Lat	Lon
38878	61.7	-176
38879	62	-174
38880	62	-174
38881	62	-175
38882	62	-176
38883	54.7	-165

4.2 Extrapolation grid

We also generate the extrapolation grid appropriate for a given region. For new regions, we use `Region="Other"`.

```
Extrapolation_List = SpatialDeltaGLMM::Prepare_Extrapolation_Data_Fn(Region = Region,
    strata.limits = strata.limits)
```

4.3 Derived objects for spatio-temporal estimation

And we finally generate the information used for conducting spatio-temporal parameter estimation, bundled in list `Spatial_List`

```
Spatial_List = SpatialDeltaGLMM::Spatial_Information_Fn(grid_size_km = grid_size_km,
    n_x = n_x, Method = Method, Lon = Data_Geostat[,
        "Lon"], Lat = Data_Geostat[, "Lat"], Extrapolation_List = Extrapolation_List,
    randomseed = Kmeans_Config[["randomseed"]], nstart = Kmeans_Config[["nstart"]],
    iter.max = Kmeans_Config[["iter.max"]], DirPath = DateFile,
```

```
    Save_Results = FALSE)
# Add knots to Data_Geostat
Data_Geostat = cbind(Data_Geostat, knot_i = Spatial_List$knot_i)
```

5 Build and run model

5.1 Build model

To estimate parameters, we first build a list of data-inputs used for parameter estimation. `Data_Fn` has some simple checks for buggy inputs, but also please read the help file `?Data_Fn`.

```
TmbData = Data_Fn(Version = Version, FieldConfig = FieldConfig,
    OverdispersionConfig = OverdispersionConfig, RhoConfig = RhoConfig,
    ObsModel = ObsModel, c_i = as.numeric(Data_Geostat[,
        "spp"]) - 1, b_i = Data_Geostat[, "Catch_KG"],
    a_i = Data_Geostat[, "AreaSwept_km2"], v_i = as.numeric(Data_Geostat[,
        "Vessel"]) - 1, s_i = Data_Geostat[, "knot_i"] -
        1, t_i = Data_Geostat[, "Year"], a_xl = Spatial_List$a_xl,
    MeshList = Spatial_List$MeshList, GridList = Spatial_List$GridList,
    Method = Spatial_List$Method, Options = Options)
```

We then build the TMB object.

```
TmbList = Build_TMB_Fn(TmbData = TmbData, RunDir = DateFile,
    Version = Version, RhoConfig = RhoConfig, loc_x = Spatial_List$loc_x,
    Method = Method)
Obj = TmbList[["Obj"]]
```

5.2 Estimate fixed effects and predict random effects

Next, we use a gradient-based nonlinear minimizer to identify maximum likelihood estimates for fixed-effects

```
Opt = TMBhelper::Optimize(obj = Obj, lower = TmbList[["Lower"]],
    upper = TmbList[["Upper"]], getsd = TRUE, savedir = DateFile,
    bias.correct = FALSE)
```

Finally, we bundle and save output

```
Report = Obj$report()
Save = list("Opt"=Opt, "Report"=Report, "ParHat"=Obj$env$parList(Opt$par), "TmbData"=TmbData)
save(Save, file=paste0(DateFile,"Save.RData"))
```

6 Diagnostic plots

We first apply a set of standard model diagnostics to confirm that the model is reasonable and deserves further attention. If any of these do not look reasonable, the model output should not be interpreted or used.

6.1 Plot data

It is always good practice to conduct exploratory analysis of data. Here, I visualize the spatial distribution of data. Spatio-temporal models involve the assumption that the probability of sampling a given location is statistically independent of the probability distribution for the response at that location. So if sampling "follows" changes in density, then the model is probably not appropriate!

```
SpatialDeltaGLMM::Plot_data_and_knots(Extrapolation_List = Extrapolation_List,
    Spatial_List = Spatial_List, Data_Geostat = Data_Geostat,
    PlotDir = DateFile)
```

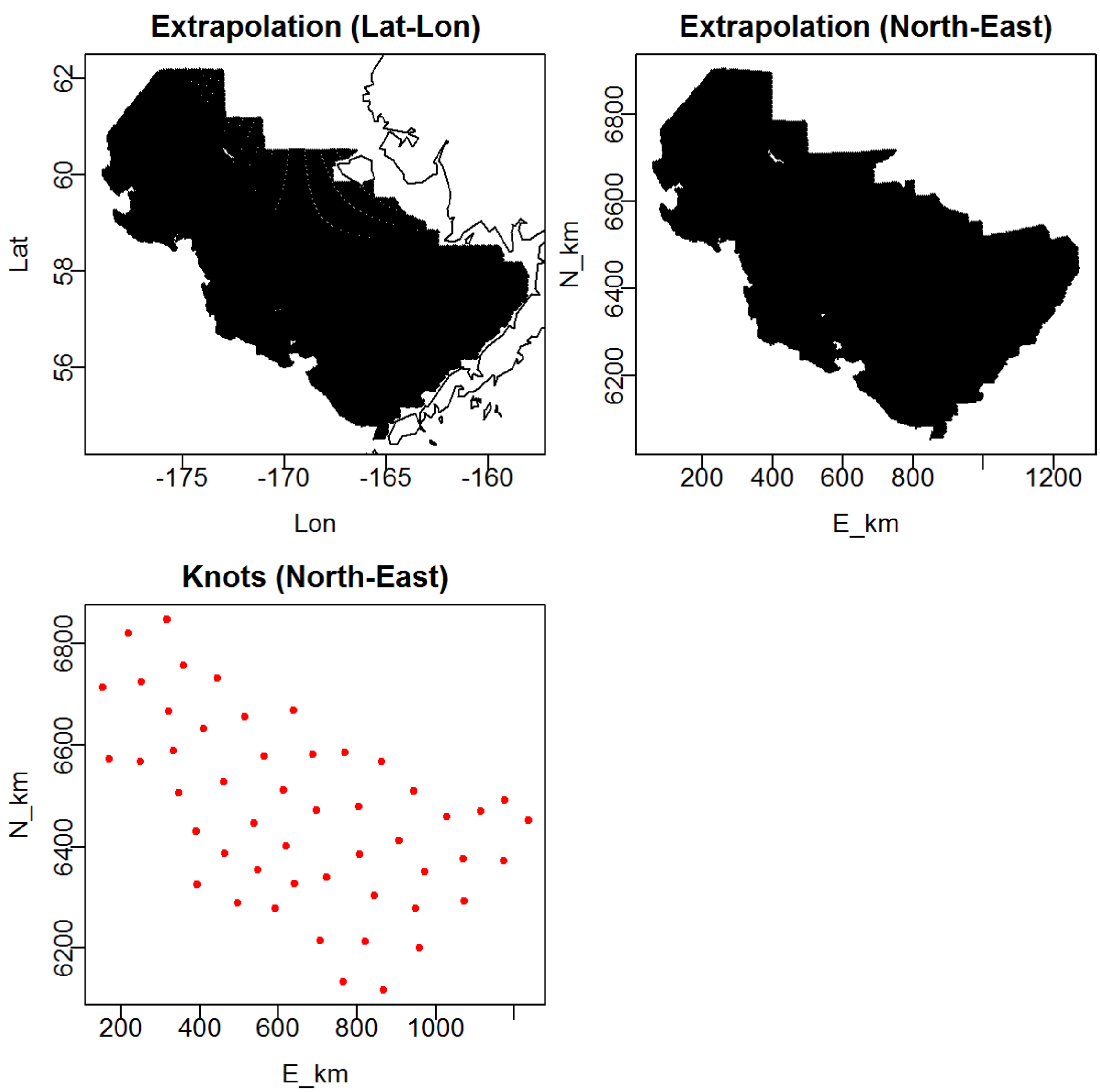

Figure 1: Spatial extent and location of knots

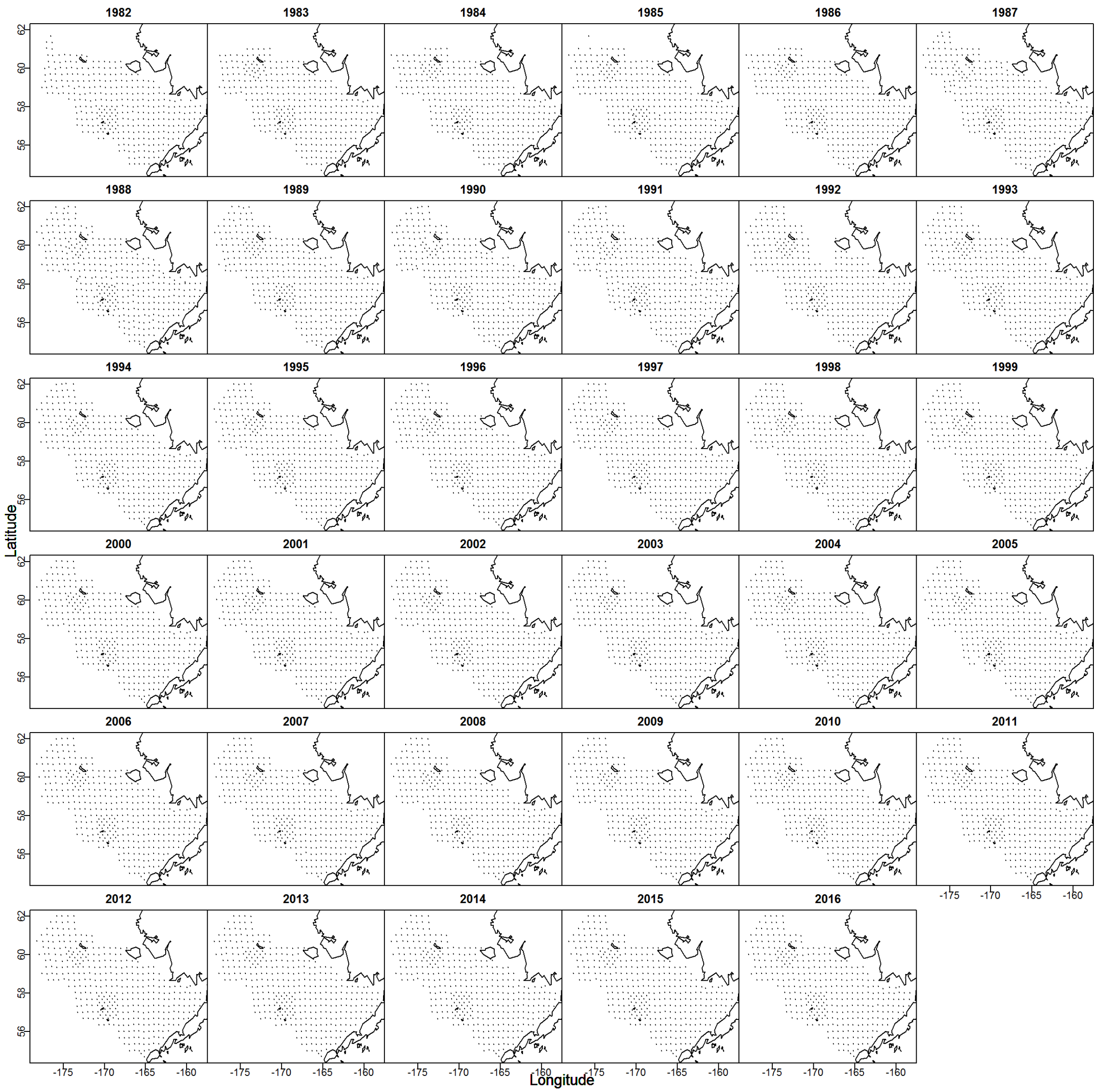

Figure 2: Spatial distribution of catch-rate data

6.2 Convergence

Here I print the diagnostics generated during parameter estimation, and I confirm that (1) no parameter is hitting an upper or lower bound and (2) the final gradient for each fixed-effect is close to zero. For explanation of parameters, please see `?Data_Fn`.

```
pander::pandoc.table( Opt$diagnostics[,c('Param','Lower','MLE','Upper','final_gradient')] )
```

Param	Lower	MLE	Upper	final_gradient
ln_H_input	-50	0.3356	50	-0.0005976
ln_H_input	-50	-1.154	50	-5.422e-05
beta1_ct	-50	-1.256	50	6.005e-05
beta1_ct	-50	3.847	50	0.0002429
beta1_ct	-50	3.088	50	-0.0002229
beta1_ct	-50	-0.8954	50	3.219e-05
beta1_ct	-50	3.842	50	4.368e-05
beta1_ct	-50	3.443	50	8.018e-05
beta1_ct	-50	-1.399	50	-8.284e-06
beta1_ct	-50	3.896	50	6.774e-05
beta1_ct	-50	2.834	50	-6.091e-05
beta1_ct	-50	-1.464	50	-3.266e-05
beta1_ct	-50	4.54	50	-4.33e-05
beta1_ct	-50	2.843	50	0.0001158
beta1_ct	-50	-1.277	50	-0.0001446
beta1_ct	-50	4.896	50	-0.0001739
beta1_ct	-50	2.457	50	0.0002654
beta1_ct	-50	0.2563	50	-2.72e-05
beta1_ct	-50	3.699	50	-6.534e-05
beta1_ct	-50	2.442	50	8.637e-05
beta1_ct	-50	-0.5265	50	1.203e-05
beta1_ct	-50	4.554	50	3.967e-05
beta1_ct	-50	2.077	50	-7.458e-05
beta1_ct	-50	0.3134	50	8.048e-05
beta1_ct	-50	3.694	50	-0.0001638
beta1_ct	-50	2.589	50	-0.0001525
beta1_ct	-50	-0.7502	50	-1.994e-05
beta1_ct	-50	3.89	50	-4.332e-05
beta1_ct	-50	2.846	50	5.38e-06
beta1_ct	-50	-1.036	50	-2.189e-05
beta1_ct	-50	5.499	50	-2.631e-06
beta1_ct	-50	2.747	50	-1.919e-05
beta1_ct	-50	-2.359	50	-6.43e-05
beta1_ct	-50	4.066	50	-5.71e-05
beta1_ct	-50	3.019	50	7.665e-05
beta1_ct	-50	0.05998	50	6.155e-05
beta1_ct	-50	4.744	50	7.107e-05
beta1_ct	-50	3.204	50	-8.611e-05
beta1_ct	-50	-1.514	50	1.585e-05
beta1_ct	-50	5.166	50	-8.582e-06
beta1_ct	-50	2.976	50	-5.843e-05
beta1_ct	-50	-2.512	50	-9.477e-05
beta1_ct	-50	4.392	50	-3.984e-05
beta1_ct	-50	2.425	50	0.0001723

Param	Lower	MLE	Upper	final_gradient
beta1_ct	-50	-0.5554	50	2.438e-05
beta1_ct	-50	4.644	50	-6.516e-05
beta1_ct	-50	3.08	50	3.612e-05
beta1_ct	-50	-1.831	50	-2.114e-05
beta1_ct	-50	4.309	50	-4.588e-05
beta1_ct	-50	3.285	50	9.433e-05
beta1_ct	-50	-0.6576	50	0.0001141
beta1_ct	-50	4.576	50	-3.299e-05
beta1_ct	-50	4.611	50	-0.0001301
beta1_ct	-50	-3.12	50	-2.492e-05
beta1_ct	-50	5.698	50	2.523e-05
beta1_ct	-50	1.881	50	6.396e-05
beta1_ct	-50	-1.363	50	1.304e-05
beta1_ct	-50	4.671	50	-0.0001789
beta1_ct	-50	2.711	50	0.000131
beta1_ct	-50	-0.3358	50	6.678e-05
beta1_ct	-50	5.225	50	2.814e-05
beta1_ct	-50	3.141	50	-5.756e-05
beta1_ct	-50	0.1005	50	-3.239e-07
beta1_ct	-50	4.328	50	-1.471e-06
beta1_ct	-50	2.858	50	9.371e-06
beta1_ct	-50	2.384	50	4.168e-05
beta1_ct	-50	4.118	50	2.801e-05
beta1_ct	-50	2.89	50	-7.295e-05
beta1_ct	-50	1.847	50	2.649e-05
beta1_ct	-50	4.999	50	-9.449e-05
beta1_ct	-50	2.758	50	7.801e-05
beta1_ct	-50	3.082	50	3.154e-05
beta1_ct	-50	4.291	50	5.369e-05
beta1_ct	-50	3.163	50	-5.176e-05
beta1_ct	-50	-0.004854	50	4.52e-05
beta1_ct	-50	4.128	50	0.0001009
beta1_ct	-50	2.135	50	-0.0001473
beta1_ct	-50	-0.5614	50	-0.0001267
beta1_ct	-50	3.75	50	-0.0001092
beta1_ct	-50	2.331	50	0.0002248
beta1_ct	-50	-0.4671	50	-0.0001174
beta1_ct	-50	2.55	50	0.000312
beta1_ct	-50	2.099	50	0.0001634
beta1_ct	-50	-1.429	50	-7.831e-05
beta1_ct	-50	3.045	50	-0.0001006
beta1_ct	-50	1.444	50	-8.12e-05
beta1_ct	-50	-0.8585	50	-1.144e-05
beta1_ct	-50	2.642	50	0.0003487
beta1_ct	-50	2.099	50	-8.635e-05
beta1_ct	-50	1.079	50	3.81e-05
beta1_ct	-50	4.284	50	2.679e-05
beta1_ct	-50	2.316	50	-0.0001219
beta1_ct	-50	-1.732	50	-1.148e-06
beta1_ct	-50	4.237	50	2.528e-06
beta1_ct	-50	1.726	50	-7.585e-05
beta1_ct	-50	-1.051	50	-2.746e-06

Param	Lower	MLE	Upper	final_gradient
beta1_ct	-50	4.7	50	-0.0001428
beta1_ct	-50	2.166	50	1.356e-05
beta1_ct	-50	1.023	50	5.241e-05
beta1_ct	-50	5.749	50	9.295e-06
beta1_ct	-50	2.392	50	-7.814e-05
beta1_ct	-50	0.7604	50	4.61e-05
beta1_ct	-50	6.856	50	1.449e-05
beta1_ct	-50	2.352	50	-2.939e-05
beta1_ct	-50	3.608	50	-2.58e-05
beta1_ct	-50	5.686	50	-2.919e-05
beta1_ct	-50	3.241	50	0.0001365
L_omega1_z	-50	3.405	50	-0.0003694
L_omega1_z	-50	0.268	50	-0.0004625
L_omega1_z	-50	2.16	50	-0.0001094
L_omega1_z	-50	2.358	50	0.0002814
L_omega1_z	-50	0.9883	50	0.0003605
L_omega1_z	-50	1.268	50	4.905e-06
L_epsilon1_z	-50	-0.9849	50	0.0007222
L_epsilon1_z	-50	0.08928	50	0.0002301
L_epsilon1_z	-50	0.6911	50	-0.0002349
L_epsilon1_z	-50	-0.291	50	0.00012
L_epsilon1_z	-50	0.2594	50	0.0008256
L_epsilon1_z	-50	-0.6556	50	-0.001142
logkappa1	-5.978	-4.669	-3.114	-0.001171
beta2_ct	-50	3.375	50	0.0001368
beta2_ct	-50	7.688	50	0.0001544
beta2_ct	-50	5.564	50	-0.0001701
beta2_ct	-50	3.951	50	0.0001775
beta2_ct	-50	8.968	50	-5.389e-05
beta2_ct	-50	5.757	50	0.0001011
beta2_ct	-50	4.083	50	0.0004934
beta2_ct	-50	8.212	50	-0.0002536
beta2_ct	-50	5.511	50	-6.925e-05
beta2_ct	-50	4.359	50	-0.0002286
beta2_ct	-50	8.498	50	-0.0001609
beta2_ct	-50	5.538	50	0.0005245
beta2_ct	-50	4.103	50	-0.0003569
beta2_ct	-50	8.221	50	0.0004019
beta2_ct	-50	5.642	50	-0.0004707
beta2_ct	-50	5.086	50	-0.0001439
beta2_ct	-50	8.617	50	7.775e-05
beta2_ct	-50	5.993	50	-0.000171
beta2_ct	-50	4.755	50	-9.576e-05
beta2_ct	-50	8.528	50	-0.0001645
beta2_ct	-50	6.14	50	0.0006069
beta2_ct	-50	5.004	50	-0.0005986
beta2_ct	-50	8.426	50	0.0001585
beta2_ct	-50	6.062	50	-0.0001348
beta2_ct	-50	4.951	50	-0.0008462
beta2_ct	-50	8.335	50	-0.000333
beta2_ct	-50	6.232	50	0.0008426
beta2_ct	-50	4.496	50	-0.0003297

Param	Lower	MLE	Upper	final_gradient
beta2__ct	-50	8.387	50	-0.0002358
beta2__ct	-50	6.195	50	0.001108
beta2__ct	-50	4.685	50	0.0002811
beta2__ct	-50	8.173	50	0.0003046
beta2__ct	-50	6.177	50	-0.0006135
beta2__ct	-50	5.38	50	-0.0004471
beta2__ct	-50	8.537	50	-2.149e-06
beta2__ct	-50	6.325	50	-0.0001673
beta2__ct	-50	5.522	50	0.001133
beta2__ct	-50	8.303	50	0.0001682
beta2__ct	-50	6.319	50	-0.001035
beta2__ct	-50	5.185	50	0.0001135
beta2__ct	-50	7.958	50	2.462e-05
beta2__ct	-50	6.053	50	-0.0001106
beta2__ct	-50	5.618	50	9.616e-05
beta2__ct	-50	8.008	50	-0.0001202
beta2__ct	-50	6.273	50	0.0002968
beta2__ct	-50	5.094	50	0.000263
beta2__ct	-50	8.13	50	0.0001078
beta2__ct	-50	6.4	50	-8.665e-05
beta2__ct	-50	5.083	50	-0.00014
beta2__ct	-50	7.862	50	0.0001059
beta2__ct	-50	6.375	50	-0.0002616
beta2__ct	-50	4.219	50	7.002e-05
beta2__ct	-50	7.763	50	-2.596e-06
beta2__ct	-50	5.521	50	-0.0001426
beta2__ct	-50	4.899	50	0.001515
beta2__ct	-50	8.403	50	0.0002128
beta2__ct	-50	5.9	50	-0.001467
beta2__ct	-50	5.045	50	-0.0002816
beta2__ct	-50	8.479	50	-2.238e-06
beta2__ct	-50	6.044	50	0.0001186
beta2__ct	-50	4.722	50	-0.0002251
beta2__ct	-50	8.307	50	9.979e-05
beta2__ct	-50	6.16	50	0.000136
beta2__ct	-50	5.621	50	-0.0001763
beta2__ct	-50	8.844	50	-2.24e-05
beta2__ct	-50	6.061	50	0.000402
beta2__ct	-50	5.755	50	-0.0001386
beta2__ct	-50	8.348	50	-2.262e-05
beta2__ct	-50	6.33	50	0.0001257
beta2__ct	-50	6.126	50	0.0001328
beta2__ct	-50	8.204	50	-0.0003918
beta2__ct	-50	6.328	50	0.0006973
beta2__ct	-50	5.382	50	0.0001319
beta2__ct	-50	7.537	50	0.0002067
beta2__ct	-50	6.052	50	-0.0003622
beta2__ct	-50	5.03	50	-0.0007385
beta2__ct	-50	7.382	50	7.387e-05
beta2__ct	-50	5.984	50	0.0001469
beta2__ct	-50	5.28	50	-0.000235
beta2__ct	-50	7.04	50	0.0002199

Param	Lower	MLE	Upper	final_gradient
beta2_ct	-50	5.734	50	-0.0003654
beta2_ct	-50	4.73	50	-0.0002531
beta2_ct	-50	6.569	50	-0.0006107
beta2_ct	-50	5.223	50	0.001196
beta2_ct	-50	5.576	50	-0.0008707
beta2_ct	-50	7.547	50	-9.717e-05
beta2_ct	-50	5.529	50	0.0005499
beta2_ct	-50	5.459	50	0.0001386
beta2_ct	-50	7.672	50	9.586e-05
beta2_ct	-50	5.711	50	0.0002853
beta2_ct	-50	5.127	50	0.001385
beta2_ct	-50	7.666	50	-0.0003882
beta2_ct	-50	5.537	50	-0.0007551
beta2_ct	-50	5.178	50	0.0006595
beta2_ct	-50	7.772	50	2.46e-05
beta2_ct	-50	5.654	50	-0.0008002
beta2_ct	-50	5.737	50	-0.0005058
beta2_ct	-50	8.766	50	0.0003184
beta2_ct	-50	5.852	50	-0.0006576
beta2_ct	-50	5.583	50	0.0001887
beta2_ct	-50	8.959	50	-0.0001067
beta2_ct	-50	5.887	50	0.0004998
beta2_ct	-50	6.344	50	-0.0001348
beta2_ct	-50	8.877	50	-0.0001138
beta2_ct	-50	6.1	50	0.0002489
L_omega2_z	-50	-1.444	50	8.858e-05
L_omega2_z	-50	-0.7518	50	-0.0003601
L_omega2_z	-50	-0.7636	50	-0.0003125
L_omega2_z	-50	-0.8668	50	-4.385e-07
L_omega2_z	-50	-0.06517	50	-0.0002076
L_omega2_z	-50	0.6738	50	-8.546e-05
L_epsilon2_z	-50	0.5415	50	0.0006373
L_epsilon2_z	-50	0.2826	50	-0.0007017
L_epsilon2_z	-50	0.9256	50	0.001132
L_epsilon2_z	-50	0.248	50	-0.0008566
L_epsilon2_z	-50	0.1679	50	-0.002059
L_epsilon2_z	-50	-0.6256	50	-0.001682
logkappa2	-5.978	-4.298	-3.114	-5.247e-07
logSigmaM	-50	-0.01824	10	0.001435
logSigmaM	-50	0.2275	10	0.004218
logSigmaM	-50	0.04248	10	0.001392

6.3 Diagnostics for encounter-probability component

Next, we check whether observed encounter frequencies for either low or high probability samples are within the 95% predictive interval for predicted encounter probability

```
Enc_prob = SpatialDeltaGLMM::Check_encounter_prob(Report = Report,
    Data_Geostat = Data_Geostat, DirName = DateFile)
```

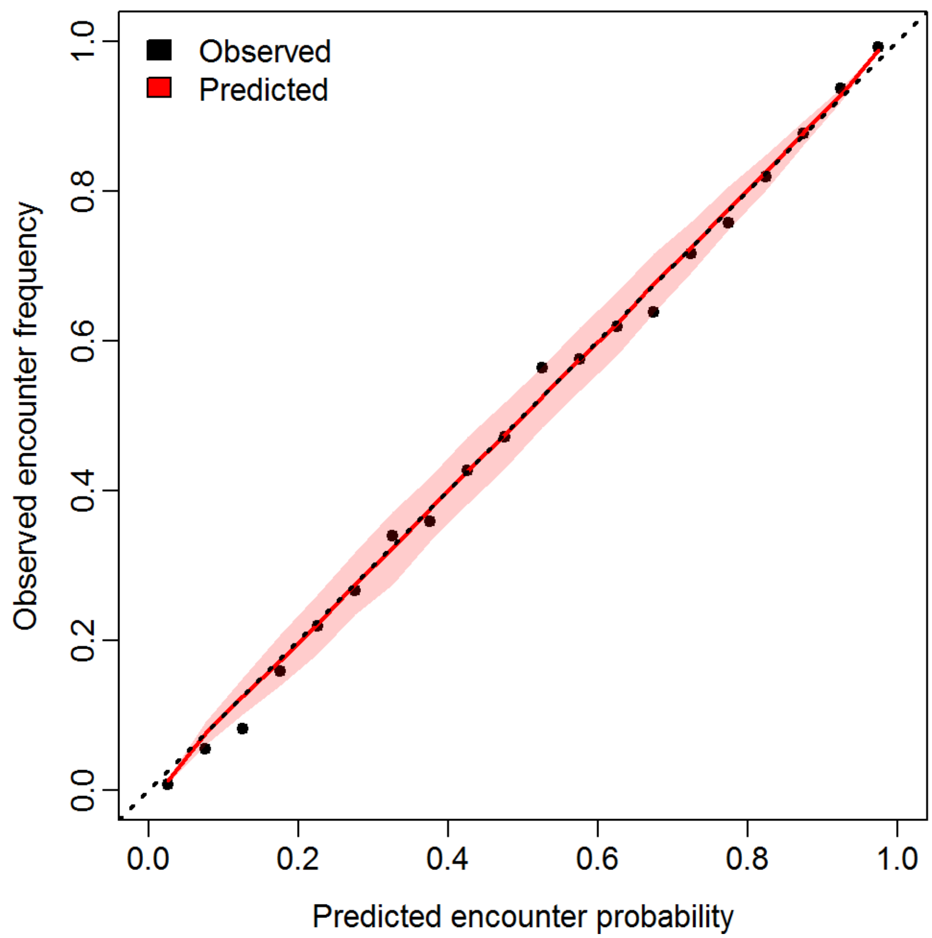

Figure 3: Expectated probability and observed frequency of encounter for “encounter probability” component

6.4 Diagnostics for positive-catch-rate component

We can visualize fit to residuals of catch-rates given encounters using a Q-Q plot. A good Q-Q plot will have residuals along the one-to-one line.

```
Q = SpatialDeltaGLMM::QQ_Fn(TmbData = TmbData, Report = Report,
    FileName_PP = paste0(DateFile, "Posterior_Predictive.jpg"),
    FileName_Phist = paste0(DateFile, "Posterior_Predictive-Histogram.jpg"),
    FileName_QQ = paste0(DateFile, "Q-Q_plot.jpg"),
    FileName_Qhist = paste0(DateFile, "Q-Q_hist.jpg"))  # SpatialDeltaGLMM::
```

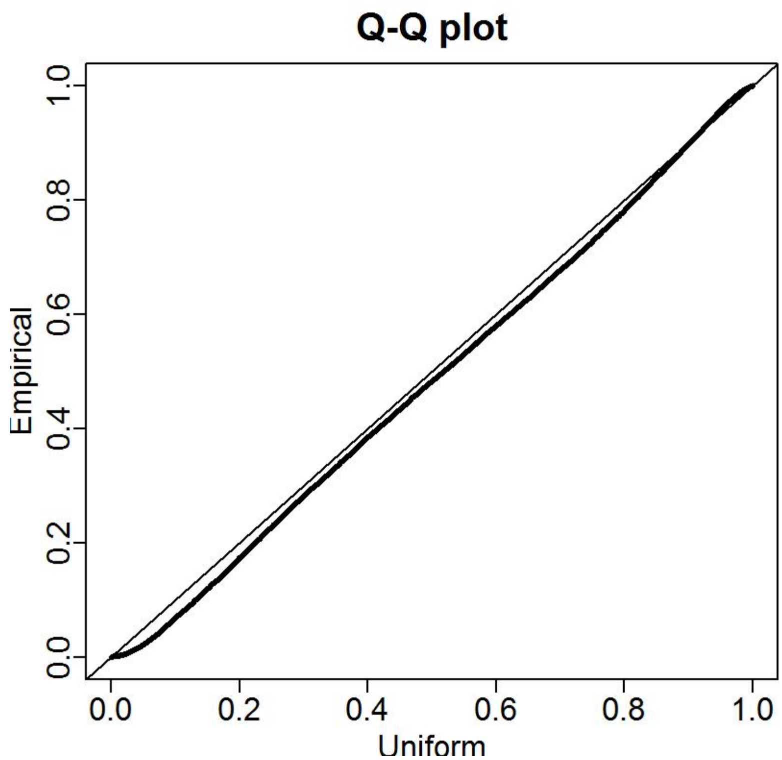

Figure 4: Quantile-quantile plot indicating residuals for "positive catch rate" component

6.5 Diagnostics for plotting residuals on a map

Finally, we visualize residuals on a map. To do so, we first define years to plot and generate plotting inputs. useful plots by first determining which years to plot (`Years2Include`), and labels for each plotted year (`Year_Set`)

```
# Get region-specific settings for plots
MapDetails_List = SpatialDeltaGLMM::MapDetails_Fn( "Region"=Region, "NN_Extrap"=Spatial_List$PolygonLis
# Decide which years to plot
Year_Set = seq(min(Data_Geostat[,'Year']),max(Data_Geostat[,'Year']))
Years2Include = which( Year_Set %in% sort(unique(Data_Geostat[,'Year'])))
```

We then plot Pearson residuals. If there are visible patterns (areas with consistently positive or negative residuals accross or within years) then this is an indication of the model "overshrinking" results towards the intercept, and model results should then be treated with caution.

```r
SpatialDeltaGLMM::plot_residuals(Lat_i = Data_Geostat[,
    "Lat"], Lon_i = Data_Geostat[, "Lon"], TmbData = TmbData,
    Report = Report, Q = Q, savedir = DateFile, MappingDetails = MapDetails_List[["MappingDetails"]],
    PlotDF = MapDetails_List[["PlotDF"]], MapSizeRatio = MapDetails_List[["MapSizeRatio"]],
    Xlim = MapDetails_List[["Xlim"]], Ylim = MapDetails_List[["Ylim"]],
    FileName = DateFile, Year_Set = Year_Set, Years2Include = Years2Include,
    Rotate = MapDetails_List[["Rotate"]], Cex = MapDetails_List[["Cex"]],
    Legend = MapDetails_List[["Legend"]], zone = MapDetails_List[["Zone"]],
    mar = c(0, 0, 2, 0), oma = c(3.5, 3.5, 0, 0), cex = 1.8)
```

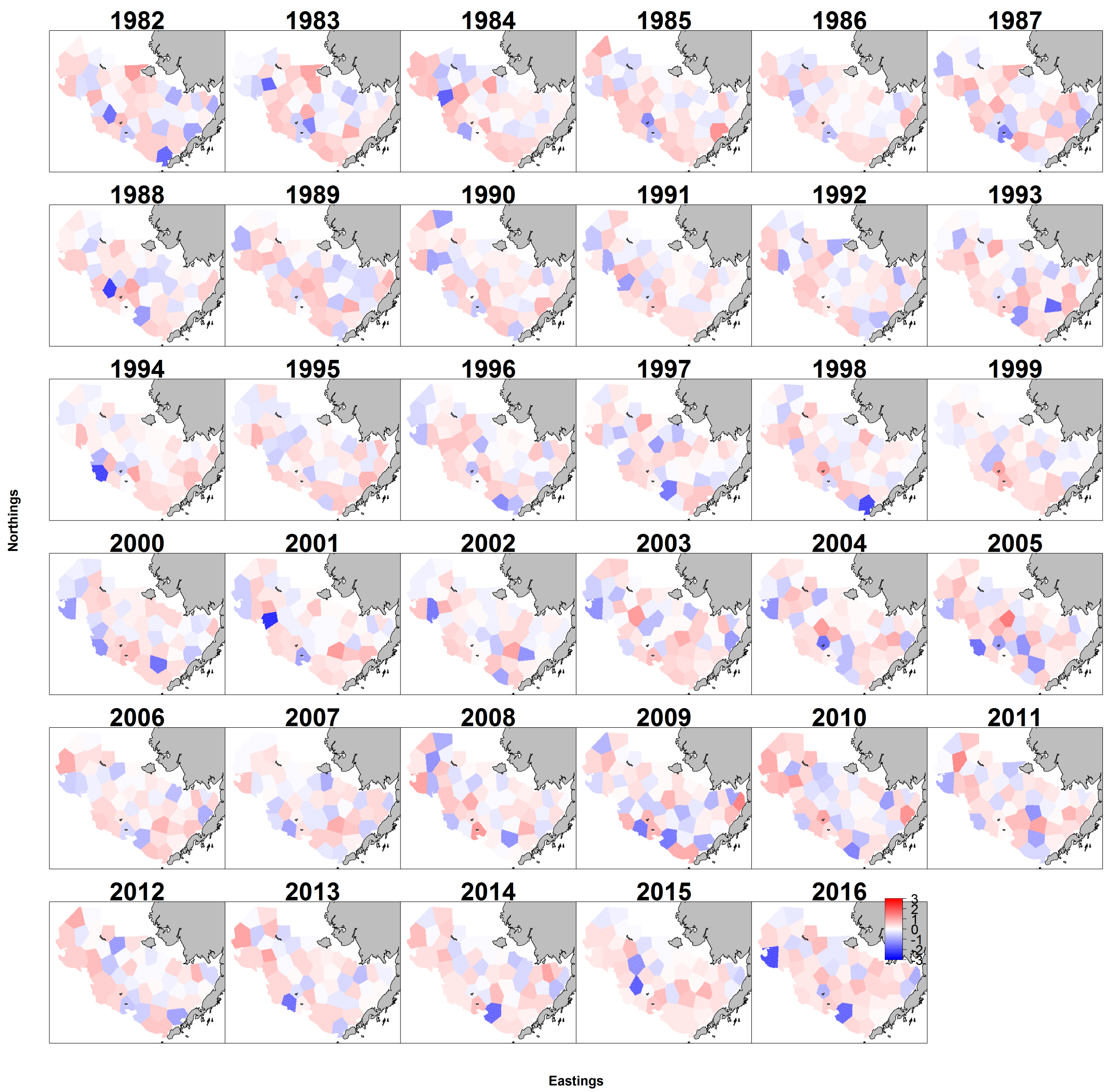

Figure 5: Pearson residuals for encounter-probability by knot

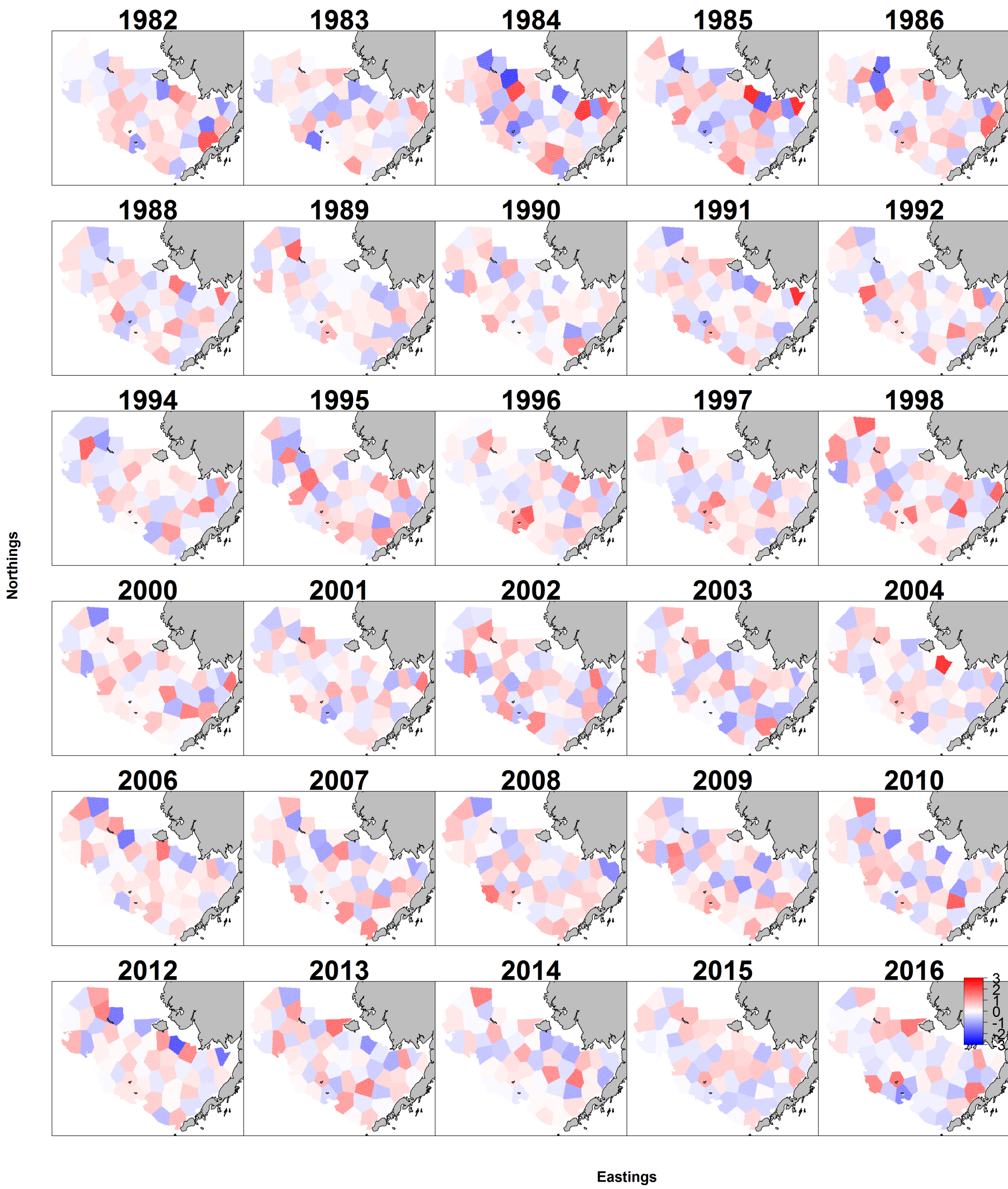

Figure 6: Pearson residuals for positive catch rates by knot

6.6 Model selection

To select among models, we recommend using the Akaike Information Criterion, AIC, via `Opt$AIC= 2.399\times 10^{5}`.

7 Model output

Last but not least, we generate pre-defined plots for visualizing results

7.1 Direction of "geometric anisotropy"

We can visualize which direction has faster or slower decorrelation (termed "geometric anisotropy")

```
SpatialDeltaGLMM::PlotAniso_Fn(FileName = paste0(DateFile,
    "Aniso.png"), Report = Report, TmbData = TmbData)
```

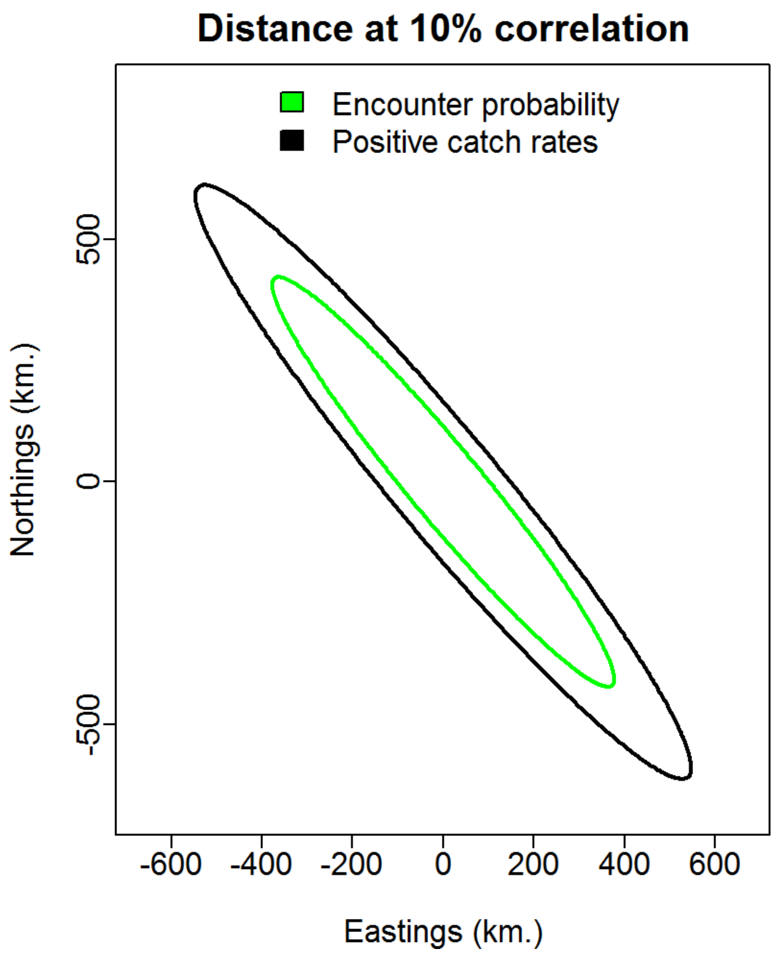

Figure 7: Decorrelation distance for different directions

7.2 Plot spatial and spatio-temporal covariance

We can visualize the spatial and spatio-temporal covariance among species in encounter probability and positive catch rates (depending upon what is turned on via `FieldConfig`):

```
Cov_List = Summarize_Covariance(Report = Report, ParHat = Obj$env$parList(),
    Data = TmbData, SD = Opt$SD, plot_cor = FALSE,
    category_names = levels(Data_Geostat[, "spp"]),
    plotdir = DateFile, plotTF = FieldConfig, mgp = c(2,
        0.5, 0), tck = -0.02, oma = c(0, 5, 2, 2))
```

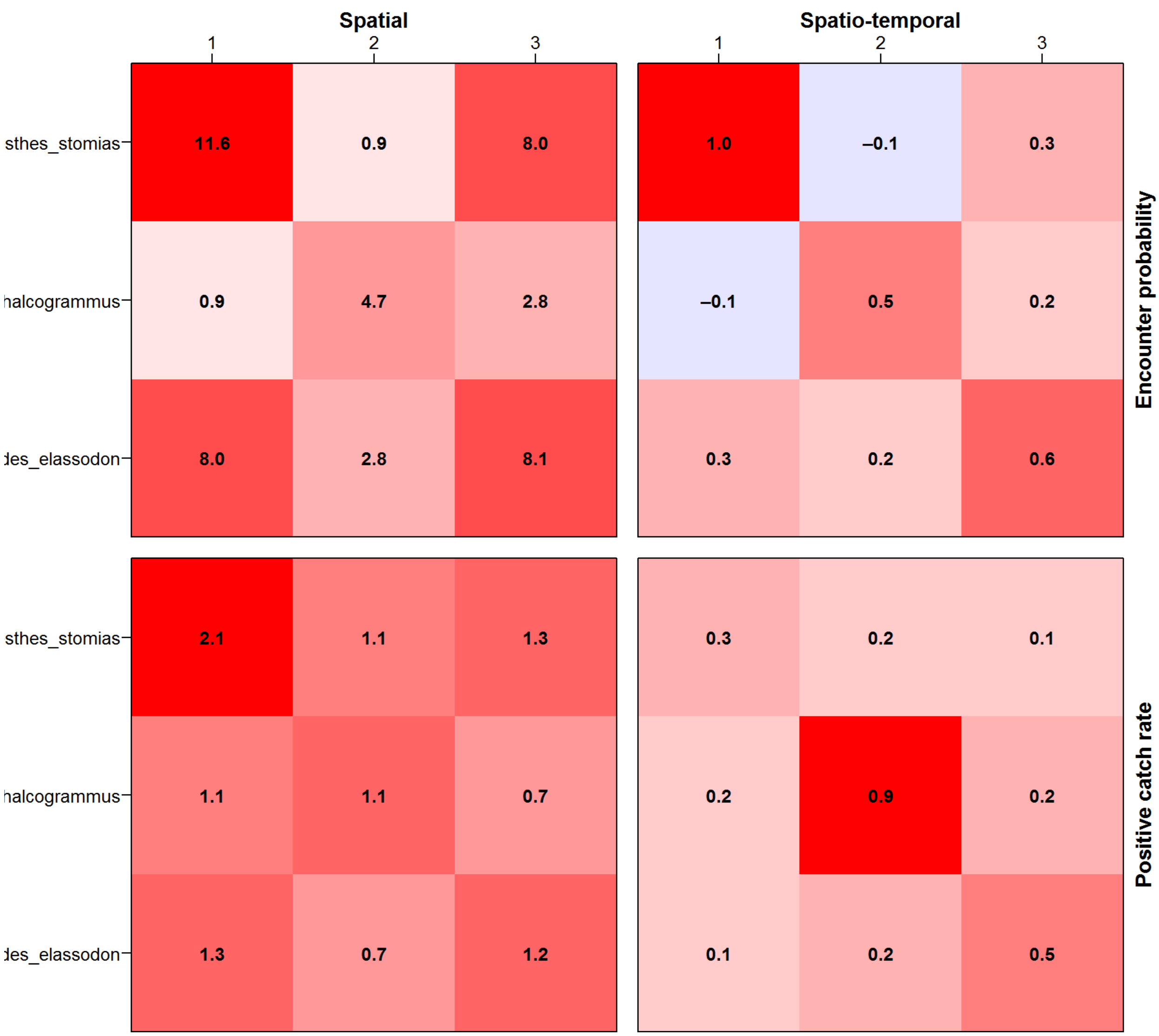

Figure 8: Spatial and spatio-temporal covariance

7.3 Density surface for each year

We can visualize many types of output from the model. Here I only show predicted density, but other options are obtained via other integers passed to `plot_set` as described in `?PlotResultsOnMap_Fn`

```
SpatialDeltaGLMM::PlotResultsOnMap_Fn(plot_set = c(3),
    MappingDetails = MapDetails_List[["MappingDetails"]],
    Report = Report, Sdreport = Opt$SD, PlotDF = MapDetails_List[["PlotDF"]],
    MapSizeRatio = MapDetails_List[["MapSizeRatio"]],
    Xlim = MapDetails_List[["Xlim"]], Ylim = MapDetails_List[["Ylim"]],
    FileName = DateFile, Year_Set = Year_Set, Years2Include = Years2Include,
    Rotate = MapDetails_List[["Rotate"]], Cex = MapDetails_List[["Cex"]],
    Legend = MapDetails_List[["Legend"]], zone = MapDetails_List[["Zone"]],
    mar = c(0, 0, 2, 0), oma = c(3.5, 3.5, 0, 0), cex = 1.8,
    category_names = levels(Data_Geostat[, "spp"]))
```

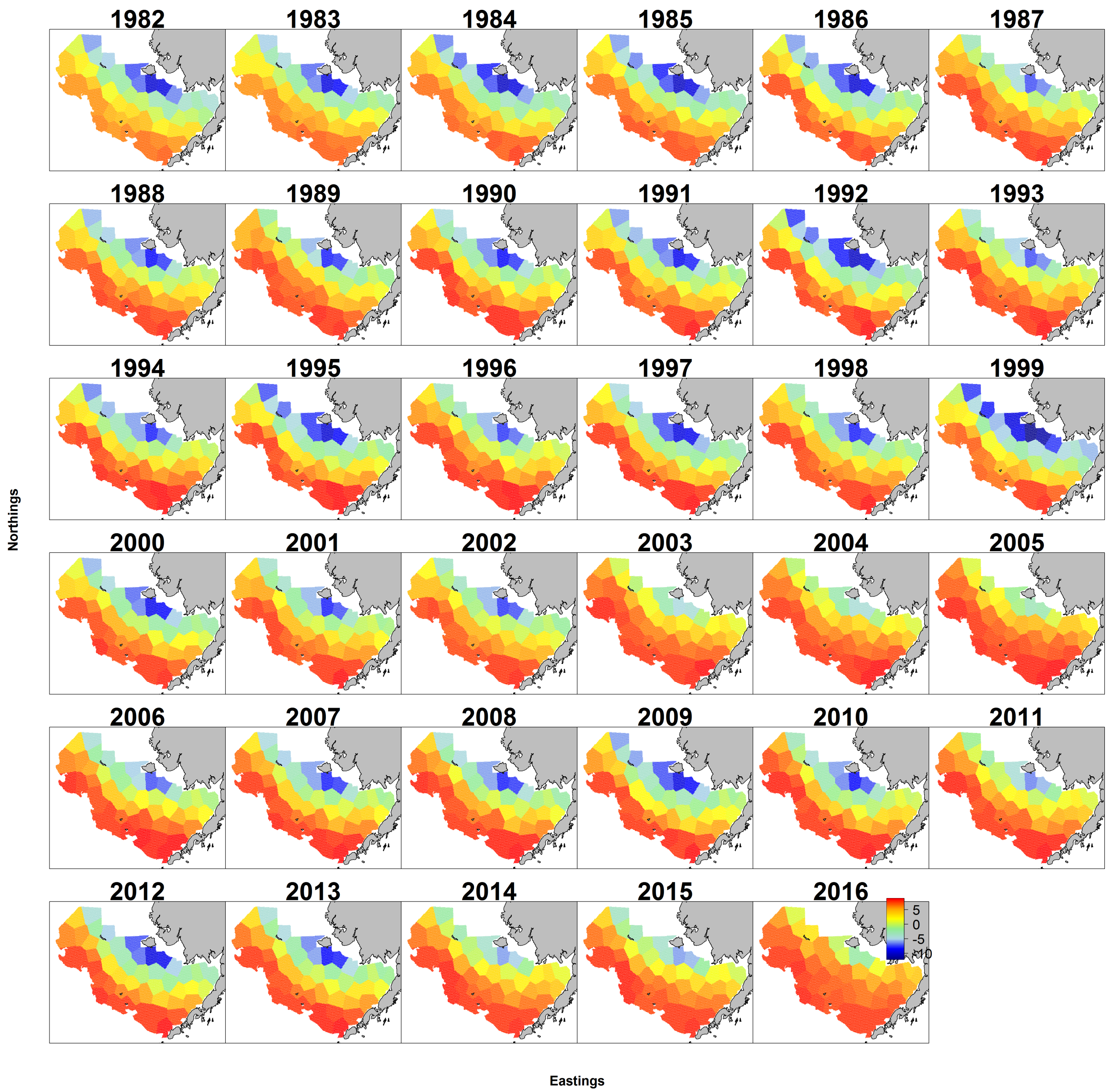

Figure 9: Density maps for each year for arrowtooth flounder

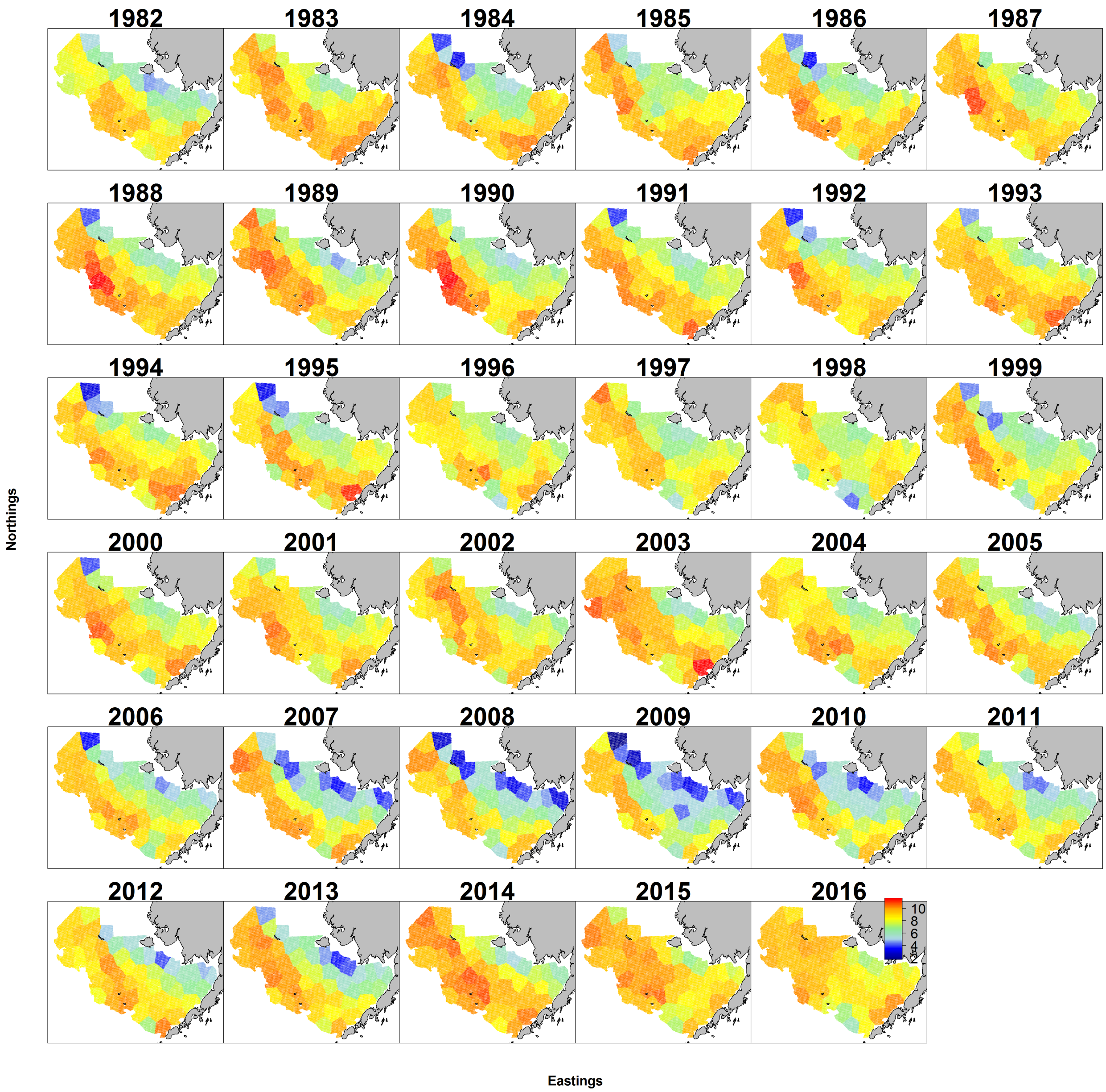

Figure 10: Density maps for each year for Alaska pollock

7.4 Index of abundance

The index of abundance is generally most useful for stock assessment models.

```
Index = SpatialDeltaGLMM::PlotIndex_Fn(DirName = DateFile,
    TmbData = TmbData, Sdreport = Opt[["SD"]], Year_Set = Year_Set,
    Years2Include = Years2Include, strata_names = strata.limits[,
        1], use_biascorr = TRUE, category_names = levels(Data_Geostat[,
        "spp"]))
pander::pandoc.table(Index$Table[, c("Category", "Year",
    "Estimate_metric_tons", "SD_mt")])
```

Category	Year	Estimate_metric_tons	SD_mt
Atheresthes_stomias	1982	64250	6689
Atheresthes_stomias	1983	97125	9268
Atheresthes_stomias	1984	144538	14117
Atheresthes_stomias	1985	159191	15511
Atheresthes_stomias	1986	192116	18334
Atheresthes_stomias	1987	282950	25800
Atheresthes_stomias	1988	286337	26542
Atheresthes_stomias	1989	329648	28784
Atheresthes_stomias	1990	371867	34531
Atheresthes_stomias	1991	263358	26139
Atheresthes_stomias	1992	291365	30620
Atheresthes_stomias	1993	413321	36091
Atheresthes_stomias	1994	456734	44291
Atheresthes_stomias	1995	391252	40100
Atheresthes_stomias	1996	486618	44812
Atheresthes_stomias	1997	387240	36275
Atheresthes_stomias	1998	306539	27454
Atheresthes_stomias	1999	185833	19306
Atheresthes_stomias	2000	277585	25497
Atheresthes_stomias	2001	342030	30674
Atheresthes_stomias	2002	276770	24311
Atheresthes_stomias	2003	497707	40160
Atheresthes_stomias	2004	514974	42567
Atheresthes_stomias	2005	693423	55143
Atheresthes_stomias	2006	559049	48919
Atheresthes_stomias	2007	446583	40009
Atheresthes_stomias	2008	477891	42434
Atheresthes_stomias	2009	362742	33808
Atheresthes_stomias	2010	520131	46941
Atheresthes_stomias	2011	498272	42279
Atheresthes_stomias	2012	365706	33920
Atheresthes_stomias	2013	380567	34986
Atheresthes_stomias	2014	469429	39297
Atheresthes_stomias	2015	414551	34492
Atheresthes_stomias	2016	521984	39352
Gadus_chalcogrammus	1982	2443413	211827
Gadus_chalcogrammus	1983	5862956	518711
Gadus_chalcogrammus	1984	4055647	354975
Gadus_chalcogrammus	1985	4608460	449561
Gadus_chalcogrammus	1986	4432969	401041

Category	Year	Estimate_metric_tons	SD_mt
Gadus_chalcogrammus	1987	4903681	455186
Gadus_chalcogrammus	1988	6549121	643655
Gadus_chalcogrammus	1989	5908851	517504
Gadus_chalcogrammus	1990	6551133	729069
Gadus_chalcogrammus	1991	4693389	420687
Gadus_chalcogrammus	1992	4243918	393319
Gadus_chalcogrammus	1993	5053485	412703
Gadus_chalcogrammus	1994	4564139	387784
Gadus_chalcogrammus	1995	4372430	393453
Gadus_chalcogrammus	1996	2800738	220331
Gadus_chalcogrammus	1997	3351566	292778
Gadus_chalcogrammus	1998	2449507	204357
Gadus_chalcogrammus	1999	3419444	334999
Gadus_chalcogrammus	2000	4638385	400685
Gadus_chalcogrammus	2001	4018528	353179
Gadus_chalcogrammus	2002	4421405	347734
Gadus_chalcogrammus	2003	7416801	663532
Gadus_chalcogrammus	2004	3691157	301272
Gadus_chalcogrammus	2005	4418679	372831
Gadus_chalcogrammus	2006	2903150	260096
Gadus_chalcogrammus	2007	3956886	405951
Gadus_chalcogrammus	2008	2759971	286115
Gadus_chalcogrammus	2009	2003803	226412
Gadus_chalcogrammus	2010	3351570	336491
Gadus_chalcogrammus	2011	2933206	265811
Gadus_chalcogrammus	2012	3271413	273255
Gadus_chalcogrammus	2013	4259455	384218
Gadus_chalcogrammus	2014	7317199	570098
Gadus_chalcogrammus	2015	6333117	485373
Gadus_chalcogrammus	2016	4589910	339786
Hippoglossoides_elassodon	1982	190158	15384
Hippoglossoides_elassodon	1983	243392	18184
Hippoglossoides_elassodon	1984	253019	20490
Hippoglossoides_elassodon	1985	246101	19249
Hippoglossoides_elassodon	1986	322159	25283
Hippoglossoides_elassodon	1987	370796	29876
Hippoglossoides_elassodon	1988	504262	39501
Hippoglossoides_elassodon	1989	470715	36459
Hippoglossoides_elassodon	1990	549520	43221
Hippoglossoides_elassodon	1991	515738	41335
Hippoglossoides_elassodon	1992	567637	44681
Hippoglossoides_elassodon	1993	578248	45517
Hippoglossoides_elassodon	1994	649206	51091
Hippoglossoides_elassodon	1995	553243	44921
Hippoglossoides_elassodon	1996	575393	45093
Hippoglossoides_elassodon	1997	711443	57595
Hippoglossoides_elassodon	1998	646763	53507
Hippoglossoides_elassodon	1999	354328	28829
Hippoglossoides_elassodon	2000	364289	27771
Hippoglossoides_elassodon	2001	466217	36078
Hippoglossoides_elassodon	2002	503611	38315
Hippoglossoides_elassodon	2003	469803	35325

Category	Year	Estimate_metric_tons	SD_mt
Hippoglossoides_elassodon	2004	573281	42320
Hippoglossoides_elassodon	2005	612228	45585
Hippoglossoides_elassodon	2006	572855	42731
Hippoglossoides_elassodon	2007	548479	42900
Hippoglossoides_elassodon	2008	488285	37764
Hippoglossoides_elassodon	2009	359245	30357
Hippoglossoides_elassodon	2010	407602	32437
Hippoglossoides_elassodon	2011	510628	43116
Hippoglossoides_elassodon	2012	346191	28211
Hippoglossoides_elassodon	2013	414886	36025
Hippoglossoides_elassodon	2014	469584	36041
Hippoglossoides_elassodon	2015	369206	27642
Hippoglossoides_elassodon	2016	427498	30173

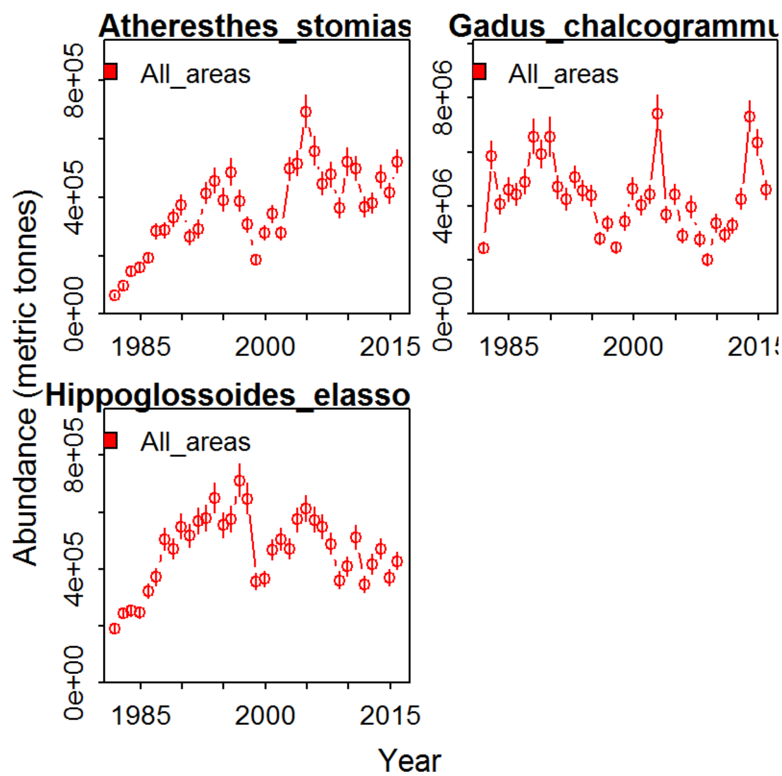

Figure 11: Index of abundance plus/minus 1 standard error

7.5 Center of gravity and range expansion/contraction

We can detect shifts in distribution or range expansion/contraction.

```
SpatialDeltaGLMM::Plot_range_shifts(Report = Report,
    TmbData = TmbData, Sdreport = Opt[["SD"]], Znames = colnames(TmbData$Z_xm),
    PlotDir = DateFile, category_names = levels(Data_Geostat[,
        "spp"]), Year_Set = Year_Set)
```

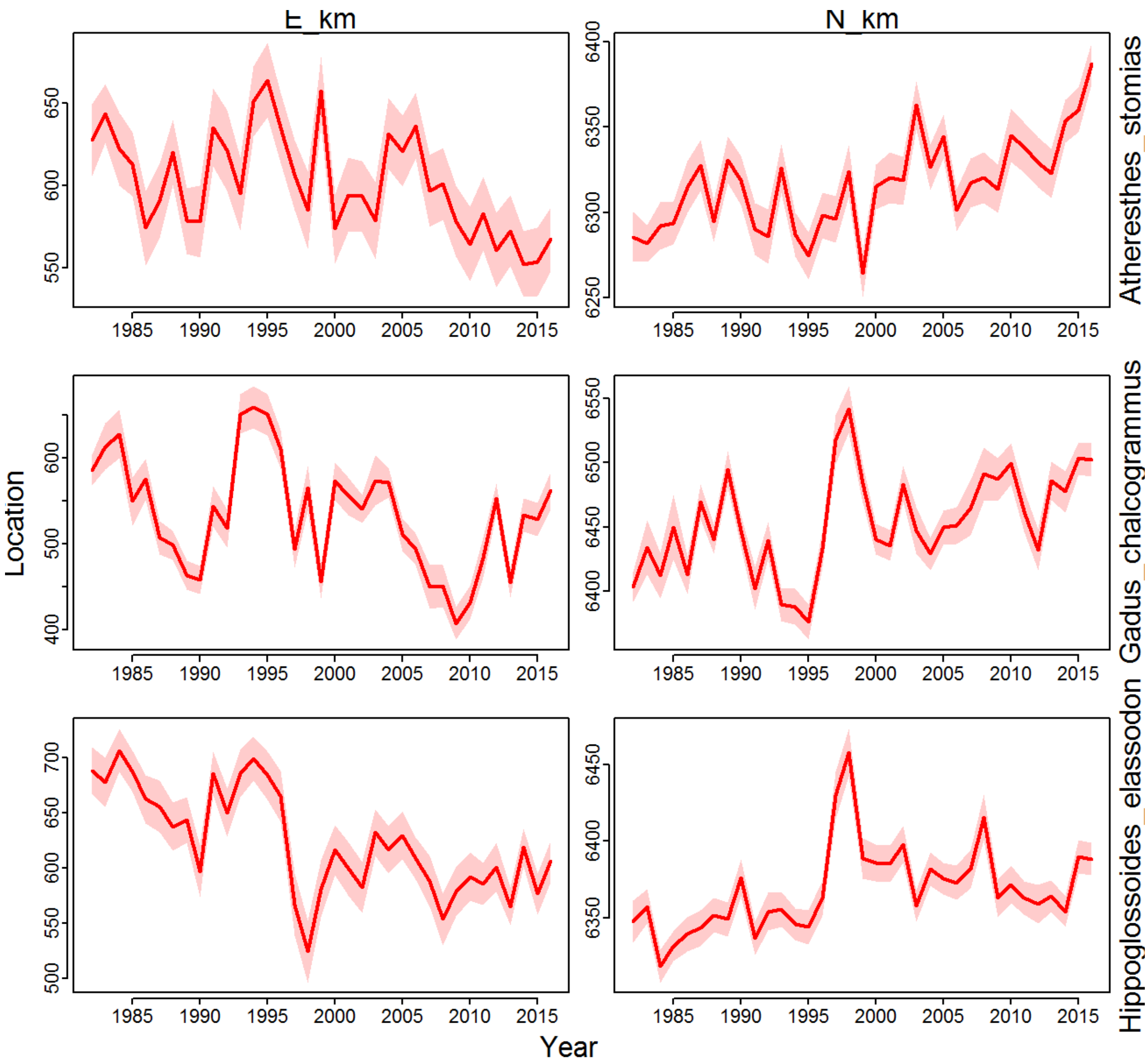

Figure 12: Center of gravity (COG) indicating shifts in distribution plus/minus 1 standard error

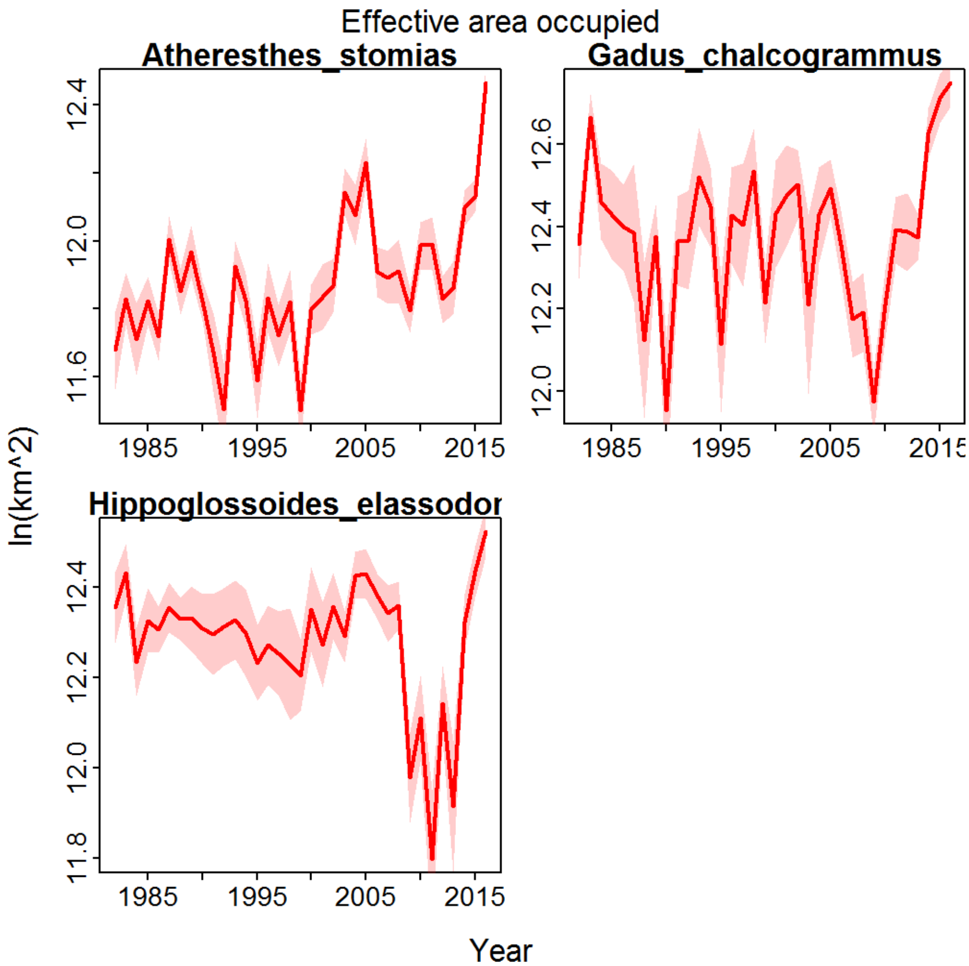

Figure 13: Effective area occupied indicating range expansion/contraction plus/minus 1 standard error

7.6 Plot overdispersion

We can also plot and inspect overdispersion (e.g., vessel effects, or tow-level fisher targetting), although this example doesn't include any.

```r
Plot_Overdispersion(filename1 = paste0(DateDir, "Overdispersion"),
    filename2 = paste0(DateDir, "Overdispersion--panel"),
    Data = TmbData, ParHat = ParHat, Report = Report,
    ControlList1 = list(Width = 5, Height = 10, Res = 200,
        Units = "in"), ControlList2 = list(Width = TmbData$n_c,
        Height = TmbData$n_c, Res = 200, Units = "in"))
```

```
## No overdispersion for presence/absence component so not generating output...

## No overdispersion for positive catch rates component so not generating output...
```

7.7 Plot factors

Finally, we can inspect the factor-decomposition for community-level patterns. This generates many plots, only some of which are included in this tutorial document.

```r
Plot_factors(Report = Report, ParHat = Obj$env$parList(),
    Data = TmbData, SD = Opt$SD, mapdetails_list = MapDetails_List,
    Year_Set = Year_Set, category_names = levels(DF[,
        "Sci"]), plotdir = DateFile)
```

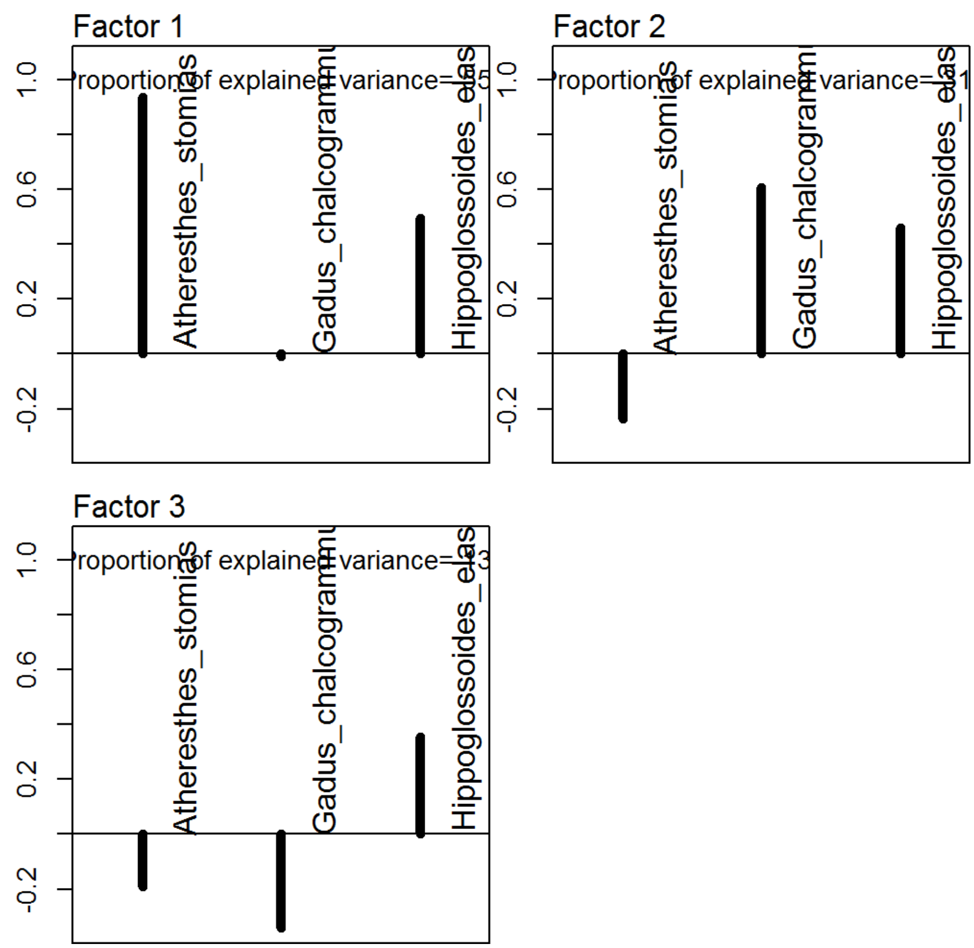

Figure 14: Factor loadings for spatio-temporal variation in encounter probability

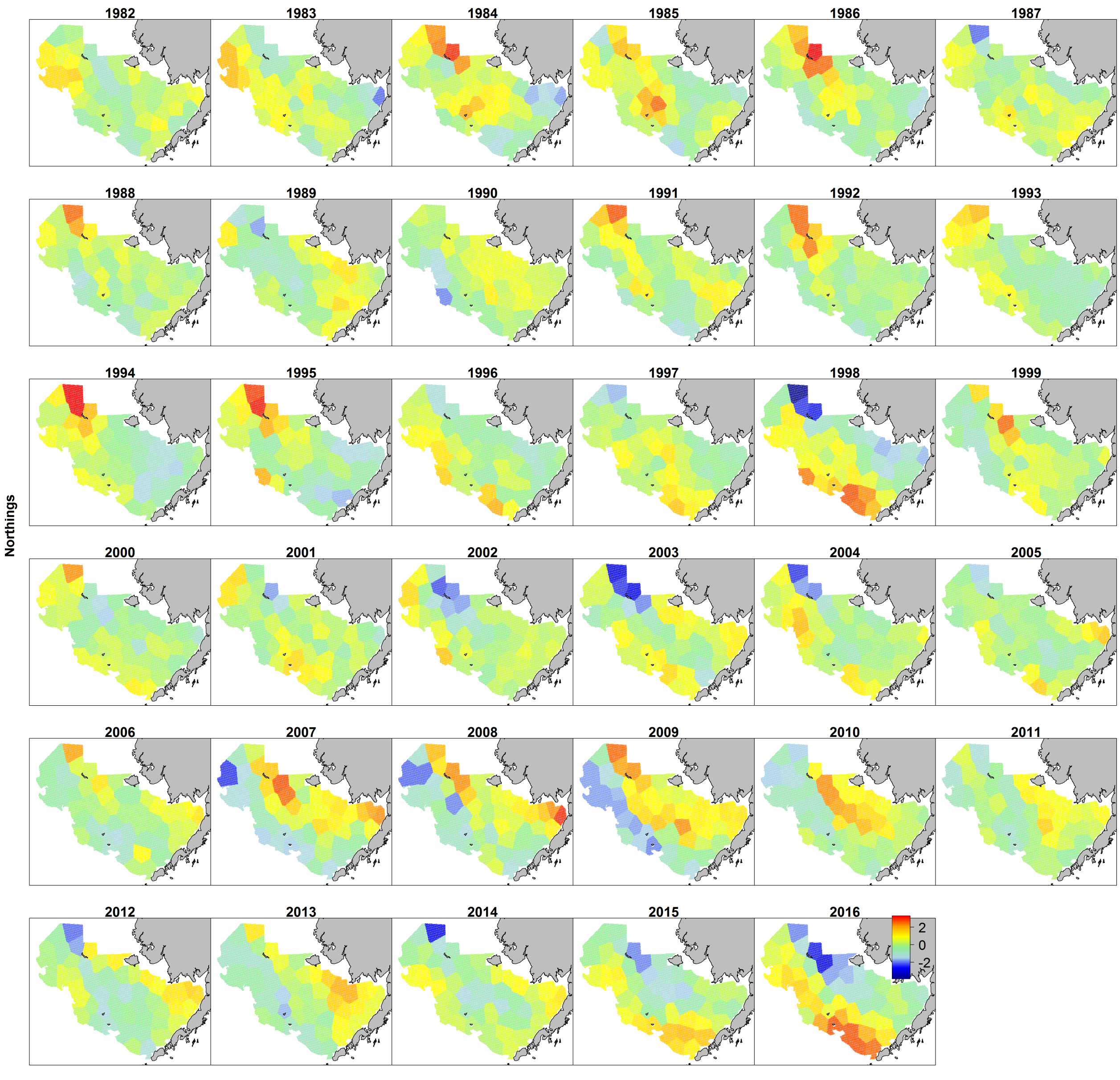

Figure 15: Factor maps for dominant (first) factor for spatio-temporal variation in positive catch rates