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

James Thorson

2017-09-17

Contents

```
## package 'pander' successfully unpacked and MD5 sums checked
##
## The downloaded binary packages are in
##  C:\Users\James.Thorson\AppData\Local\Temp\RtmpWYMb46\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)
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(Delta1 = 0, Delta2 = 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
38878	Hippoglossoides_elassodon	2016	1.15	0.01
38879	Hippoglossoides_elassodon	2016	0	0.01
38880	Hippoglossoides_elassodon	2016	0	0.01
38881	Hippoglossoides_elassodon	2016	0	0.01
38882	Hippoglossoides_elassodon	2016	0	0.01
38883	Hippoglossoides_elassodon	2016	28	0.01

	Vessel	Lat	Lon
38878	0	61.7	-176
38879	0	62	-174
38880	0	62	-174
38881	0	62	-175
38882	0	62	-176
38883	0	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)
```

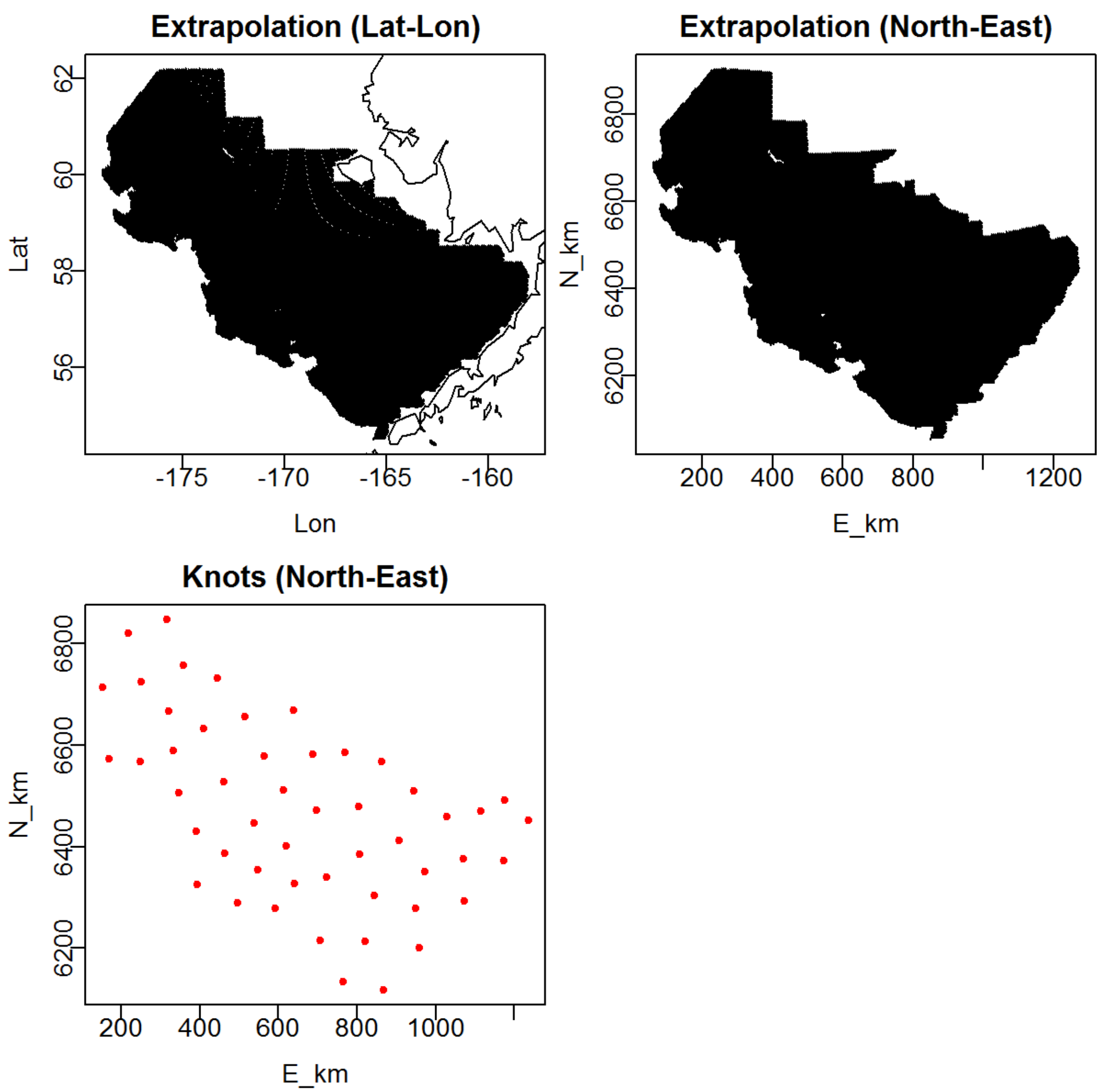

Figure 1: Spatial extent and location of knots

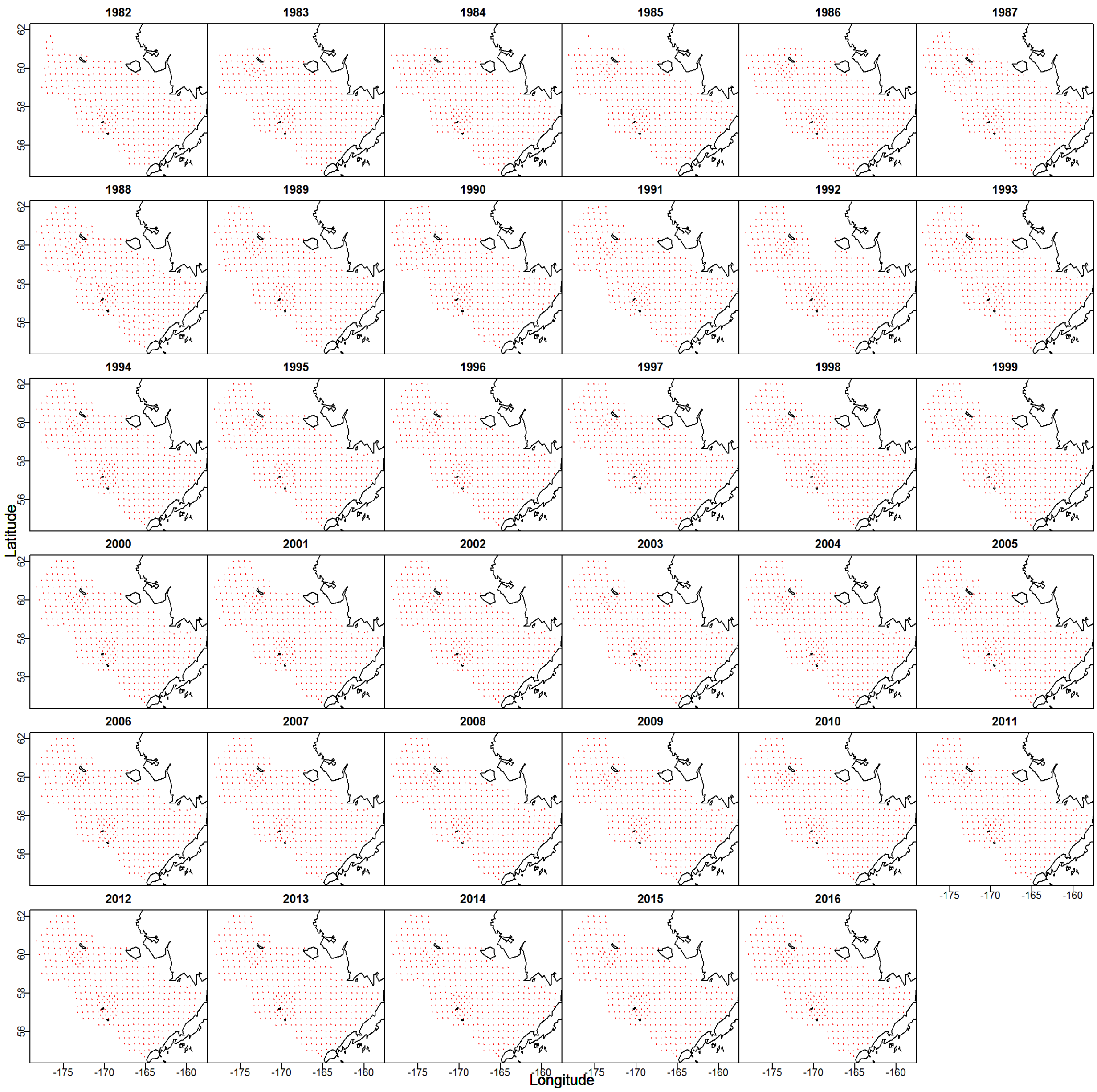

Figure 2: Spatial distribution of catch-rate data

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	-0.002135
ln_H_input	-50	-1.154	50	-0.0002868
beta1_ct	-50	-1.256	50	4.13e-05
beta1_ct	-50	3.847	50	-5.603e-05
beta1_ct	-50	3.088	50	-0.0001466
beta1_ct	-50	-0.8955	50	-3.889e-05
beta1_ct	-50	3.842	50	-0.0001119
beta1_ct	-50	3.443	50	-5.457e-05
beta1_ct	-50	-1.399	50	-6.572e-05
beta1_ct	-50	3.896	50	0.0002518
beta1_ct	-50	2.834	50	0.000198
beta1_ct	-50	-1.464	50	1.688e-05
beta1_ct	-50	4.54	50	-1.946e-06
beta1_ct	-50	2.843	50	-3.215e-05
beta1_ct	-50	-1.277	50	-4.196e-05
beta1_ct	-50	4.896	50	9.191e-05
beta1_ct	-50	2.457	50	6.044e-05
beta1_ct	-50	0.2563	50	2.1e-05
beta1_ct	-50	3.699	50	-0.0002771
beta1_ct	-50	2.442	50	-6.114e-05
beta1_ct	-50	-0.5265	50	6.571e-05
beta1_ct	-50	4.554	50	-0.0001356
beta1_ct	-50	2.077	50	-0.0001409
beta1_ct	-50	0.3134	50	-0.0001592
beta1_ct	-50	3.694	50	-0.0002242
beta1_ct	-50	2.589	50	0.0003446
beta1_ct	-50	-0.7503	50	-2.615e-05
beta1_ct	-50	3.89	50	0.0001084
beta1_ct	-50	2.846	50	2.507e-05
beta1_ct	-50	-1.036	50	1.176e-05
beta1_ct	-50	5.499	50	4.232e-05
beta1_ct	-50	2.747	50	-3.107e-05
beta1_ct	-50	-2.359	50	0.0001179
beta1_ct	-50	4.066	50	0.0003118
beta1_ct	-50	3.019	50	-9.426e-05
beta1_ct	-50	0.05997	50	4.834e-05
beta1_ct	-50	4.744	50	-0.000184
beta1_ct	-50	3.204	50	-4.416e-05
beta1_ct	-50	-1.514	50	-2.939e-05
beta1_ct	-50	5.166	50	0.0001839
beta1_ct	-50	2.976	50	5.768e-05
beta1_ct	-50	-2.512	50	1.946e-05
beta1_ct	-50	4.391	50	-0.0003537
beta1_ct	-50	2.425	50	-1.493e-05

Param	Lower	MLE	Upper	final_gradient
beta1_ct	-50	-0.5554	50	4.047e-05
beta1_ct	-50	4.644	50	-3.058e-05
beta1_ct	-50	3.08	50	-4.354e-05
beta1_ct	-50	-1.831	50	8.543e-05
beta1_ct	-50	4.309	50	-0.0001547
beta1_ct	-50	3.285	50	-0.000157
beta1_ct	-50	-0.6576	50	-0.0001265
beta1_ct	-50	4.576	50	-0.0002956
beta1_ct	-50	4.611	50	0.0002871
beta1_ct	-50	-3.12	50	1.427e-05
beta1_ct	-50	5.698	50	-7.774e-05
beta1_ct	-50	1.881	50	9.205e-06
beta1_ct	-50	-1.363	50	-2.504e-05
beta1_ct	-50	4.671	50	-0.0001404
beta1_ct	-50	2.711	50	-7.771e-06
beta1_ct	-50	-0.3359	50	-3.062e-05
beta1_ct	-50	5.225	50	0.0002388
beta1_ct	-50	3.141	50	-6.751e-06
beta1_ct	-50	0.1005	50	3.8e-05
beta1_ct	-50	4.328	50	8.706e-05
beta1_ct	-50	2.858	50	-6.825e-05
beta1_ct	-50	2.384	50	5.725e-05
beta1_ct	-50	4.118	50	-0.0001752
beta1_ct	-50	2.889	50	-0.0001952
beta1_ct	-50	1.847	50	-6.912e-05
beta1_ct	-50	4.999	50	-9.37e-07
beta1_ct	-50	2.758	50	8.92e-05
beta1_ct	-50	3.082	50	2.1e-05
beta1_ct	-50	4.291	50	0.0004549
beta1_ct	-50	3.163	50	-0.0002048
beta1_ct	-50	-0.004868	50	5.039e-05
beta1_ct	-50	4.128	50	0.0002426
beta1_ct	-50	2.135	50	-0.0001344
beta1_ct	-50	-0.5614	50	-0.0001386
beta1_ct	-50	3.75	50	-0.0003664
beta1_ct	-50	2.331	50	0.0003392
beta1_ct	-50	-0.4671	50	-0.0002707
beta1_ct	-50	2.549	50	-0.000398
beta1_ct	-50	2.099	50	0.0005859
beta1_ct	-50	-1.429	50	-4.662e-05
beta1_ct	-50	3.045	50	-0.0001144
beta1_ct	-50	1.444	50	0.0001805
beta1_ct	-50	-0.8585	50	0.0001326
beta1_ct	-50	2.642	50	0.000889
beta1_ct	-50	2.099	50	-0.0001774
beta1_ct	-50	1.079	50	0.000128
beta1_ct	-50	4.284	50	0.0001716
beta1_ct	-50	2.316	50	-0.0002662
beta1_ct	-50	-1.732	50	8.164e-05
beta1_ct	-50	4.237	50	0.0001931
beta1_ct	-50	1.726	50	-6.347e-05
beta1_ct	-50	-1.051	50	3.752e-05

Param	Lower	MLE	Upper	final_gradient
beta1_ct	-50	4.7	50	-5.33e-07
beta1_ct	-50	2.166	50	-4.26e-05
beta1_ct	-50	1.023	50	-1.057e-05
beta1_ct	-50	5.749	50	-8.397e-05
beta1_ct	-50	2.392	50	7.437e-05
beta1_ct	-50	0.7604	50	5.264e-05
beta1_ct	-50	6.856	50	1.287e-05
beta1_ct	-50	2.352	50	-0.0001035
beta1_ct	-50	3.608	50	-4.081e-05
beta1_ct	-50	5.685	50	-9.987e-05
beta1_ct	-50	3.241	50	-5.48e-05
L_omega1_z	-50	3.405	50	-0.0002608
L_omega1_z	-50	0.268	50	-0.0003826
L_omega1_z	-50	2.16	50	0.0004296
L_omega1_z	-50	2.358	50	0.0003714
L_omega1_z	-50	0.9883	50	-8.747e-05
L_omega1_z	-50	1.268	50	2.459e-05
L_epsilon1_z	-50	0.9849	50	0.001432
L_epsilon1_z	-50	-0.08928	50	-0.0006578
L_epsilon1_z	-50	-0.6911	50	0.0003327
L_epsilon1_z	-50	0.291	50	-0.001218
L_epsilon1_z	-50	-0.2594	50	-0.0002053
L_epsilon1_z	-50	0.6556	50	0.001788
logkappa1	-5.978	-4.669	-3.114	0.0005194
beta2_ct	-50	3.375	50	0.0004581
beta2_ct	-50	7.688	50	0.0003851
beta2_ct	-50	5.564	50	-0.001047
beta2_ct	-50	3.951	50	-0.0005776
beta2_ct	-50	8.968	50	-7.44e-05
beta2_ct	-50	5.757	50	0.0006708
beta2_ct	-50	4.083	50	0.001275
beta2_ct	-50	8.212	50	0.0002381
beta2_ct	-50	5.511	50	-0.001127
beta2_ct	-50	4.359	50	-0.0003998
beta2_ct	-50	8.498	50	-0.0004766
beta2_ct	-50	5.538	50	0.00115
beta2_ct	-50	4.103	50	0.000326
beta2_ct	-50	8.221	50	0.0008228
beta2_ct	-50	5.642	50	-0.00161
beta2_ct	-50	5.086	50	0.000579
beta2_ct	-50	8.617	50	-0.0007772
beta2_ct	-50	5.993	50	0.0009042
beta2_ct	-50	4.755	50	0.001498
beta2_ct	-50	8.528	50	0.0004084
beta2_ct	-50	6.14	50	-0.001322
beta2_ct	-50	5.004	50	-0.0001633
beta2_ct	-50	8.426	50	-0.0001366
beta2_ct	-50	6.062	50	0.0004725
beta2_ct	-50	4.951	50	-0.0002989
beta2_ct	-50	8.335	50	-0.0005102
beta2_ct	-50	6.232	50	0.001554
beta2_ct	-50	4.496	50	0.0009369

Param	Lower	MLE	Upper	final_gradient
beta2_ct	-50	8.387	50	-0.0001775
beta2_ct	-50	6.195	50	-0.0002842
beta2_ct	-50	4.685	50	-0.001214
beta2_ct	-50	8.173	50	-0.0004118
beta2_ct	-50	6.177	50	0.002014
beta2_ct	-50	5.38	50	0.0003716
beta2_ct	-50	8.537	50	-8.706e-05
beta2_ct	-50	6.325	50	0.0001428
beta2_ct	-50	5.522	50	-7.92e-05
beta2_ct	-50	8.303	50	0.0005256
beta2_ct	-50	6.319	50	-0.0006809
beta2_ct	-50	5.185	50	-0.0007848
beta2_ct	-50	7.958	50	-0.0001442
beta2_ct	-50	6.053	50	0.0009572
beta2_ct	-50	5.618	50	0.0002282
beta2_ct	-50	8.008	50	-0.0003175
beta2_ct	-50	6.274	50	0.0003933
beta2_ct	-50	5.094	50	-0.0007222
beta2_ct	-50	8.13	50	-0.000184
beta2_ct	-50	6.4	50	0.0007413
beta2_ct	-50	5.083	50	-0.0009074
beta2_ct	-50	7.862	50	0.0001936
beta2_ct	-50	6.375	50	8.547e-05
beta2_ct	-50	4.219	50	0.0001387
beta2_ct	-50	7.763	50	0.0001173
beta2_ct	-50	5.521	50	-6.02e-05
beta2_ct	-50	4.898	50	0.0004791
beta2_ct	-50	8.403	50	0.0006896
beta2_ct	-50	5.9	50	-0.001935
beta2_ct	-50	5.045	50	-0.0006675
beta2_ct	-50	8.479	50	-0.0005201
beta2_ct	-50	6.044	50	0.000843
beta2_ct	-50	4.722	50	0.0004218
beta2_ct	-50	8.307	50	-0.0001293
beta2_ct	-50	6.16	50	0.0001911
beta2_ct	-50	5.621	50	-0.0003875
beta2_ct	-50	8.844	50	0.0007552
beta2_ct	-50	6.061	50	-0.001294
beta2_ct	-50	5.755	50	-0.0003968
beta2_ct	-50	8.348	50	0.0007227
beta2_ct	-50	6.33	50	-0.001135
beta2_ct	-50	6.126	50	-0.0002379
beta2_ct	-50	8.205	50	0.0002822
beta2_ct	-50	6.328	50	-0.000335
beta2_ct	-50	5.382	50	0.001954
beta2_ct	-50	7.537	50	-8.369e-05
beta2_ct	-50	6.052	50	-0.001206
beta2_ct	-50	5.03	50	-0.0004771
beta2_ct	-50	7.382	50	-5.538e-05
beta2_ct	-50	5.984	50	0.0005968
beta2_ct	-50	5.28	50	-0.002473
beta2_ct	-50	7.04	50	7.118e-05

Param	Lower	MLE	Upper	final_gradient
beta2_ct	-50	5.734	50	0.001469
beta2_ct	-50	4.73	50	0.001148
beta2_ct	-50	6.569	50	-0.0001517
beta2_ct	-50	5.223	50	-0.0005879
beta2_ct	-50	5.576	50	0.001566
beta2_ct	-50	7.547	50	-0.001041
beta2_ct	-50	5.529	50	0.0006014
beta2_ct	-50	5.459	50	0.0003078
beta2_ct	-50	7.672	50	-0.0008212
beta2_ct	-50	5.711	50	0.0007741
beta2_ct	-50	5.127	50	-0.001647
beta2_ct	-50	7.666	50	0.0008092
beta2_ct	-50	5.537	50	-0.0004324
beta2_ct	-50	5.178	50	-0.0008627
beta2_ct	-50	7.772	50	0.0003971
beta2_ct	-50	5.654	50	-0.0009335
beta2_ct	-50	5.737	50	0.0004886
beta2_ct	-50	8.766	50	-0.0005001
beta2_ct	-50	5.852	50	0.0003389
beta2_ct	-50	5.583	50	-0.0007947
beta2_ct	-50	8.959	50	0.0005497
beta2_ct	-50	5.887	50	-0.001071
beta2_ct	-50	6.344	50	0.0007808
beta2_ct	-50	8.877	50	-0.000361
beta2_ct	-50	6.1	50	0.001451
L_omega2_z	-50	1.444	50	-3.938e-05
L_omega2_z	-50	0.7518	50	-0.0004496
L_omega2_z	-50	-0.7636	50	-0.001402
L_omega2_z	-50	0.8668	50	0.0003397
L_omega2_z	-50	-0.06516	50	0.001269
L_omega2_z	-50	0.6738	50	0.0008152
L_epsilon2_z	-50	0.5415	50	-0.002294
L_epsilon2_z	-50	0.2826	50	-0.001218
L_epsilon2_z	-50	-0.9256	50	0.002047
L_epsilon2_z	-50	0.248	50	-0.004188
L_epsilon2_z	-50	-0.1679	50	0.00175
L_epsilon2_z	-50	0.6256	50	-0.00387
logkappa2	-5.978	-4.298	-3.114	0.0004961
logSigmaM	-50	-0.01824	10	-0.003204
logSigmaM	-50	0.2275	10	0.006892
logSigmaM	-50	0.04248	10	-0.002621

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)
```

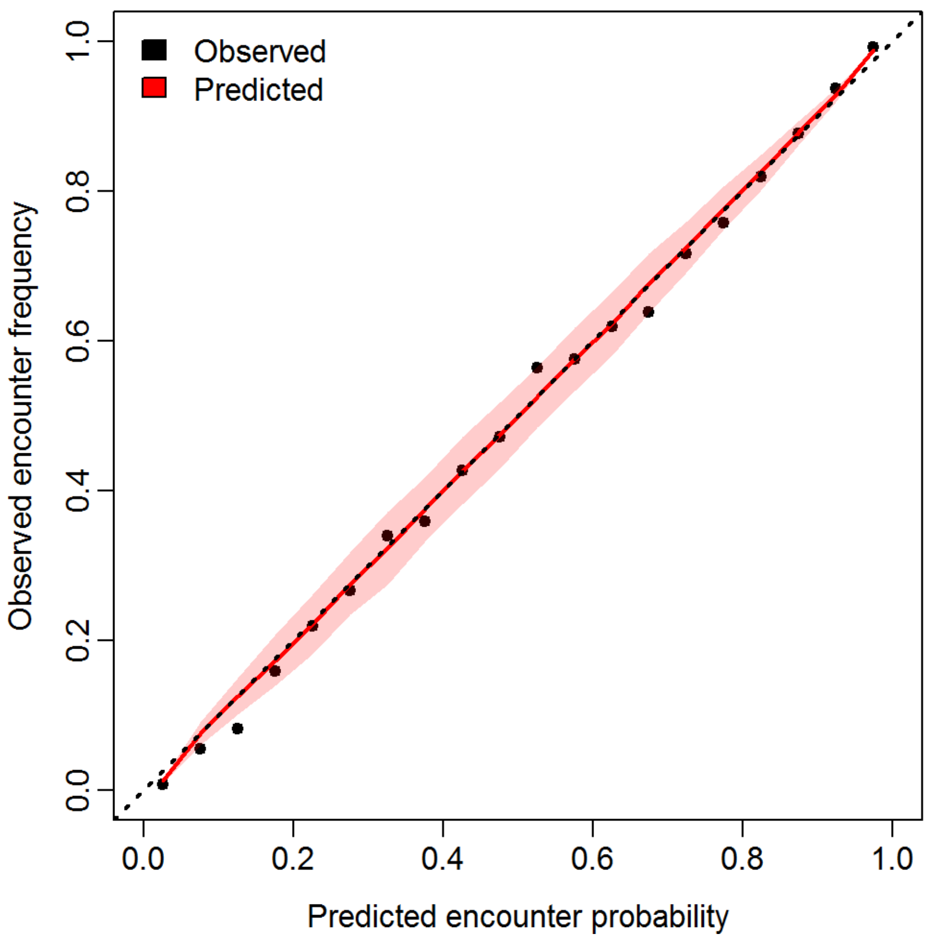

Figure 3: Expectated probability and observed frequency of encounter for “encounter probability” component

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::
```

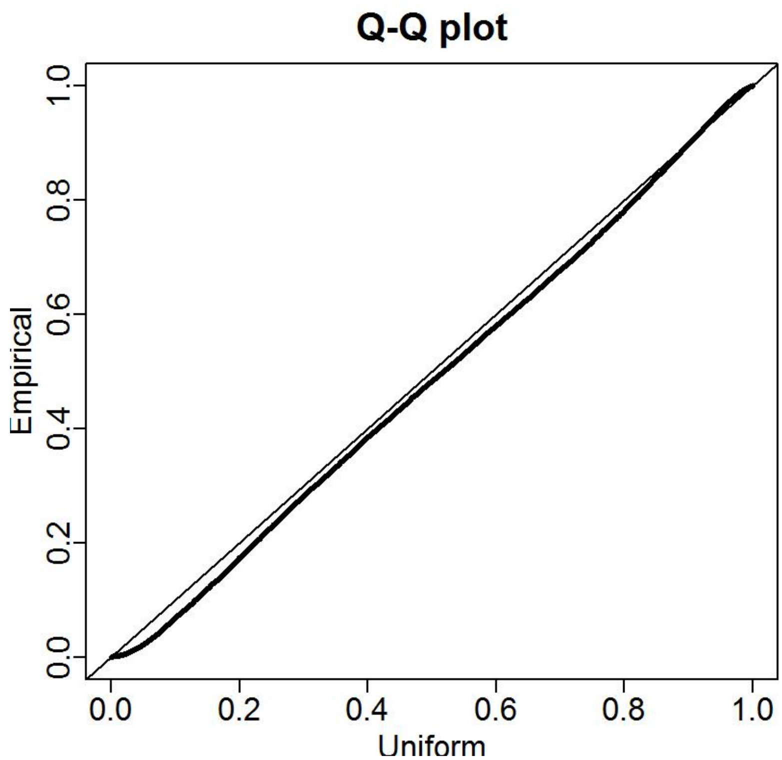

Figure 4: Quantile-quantile plot indicating residuals for "positive catch rate" component

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.

```
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)
```

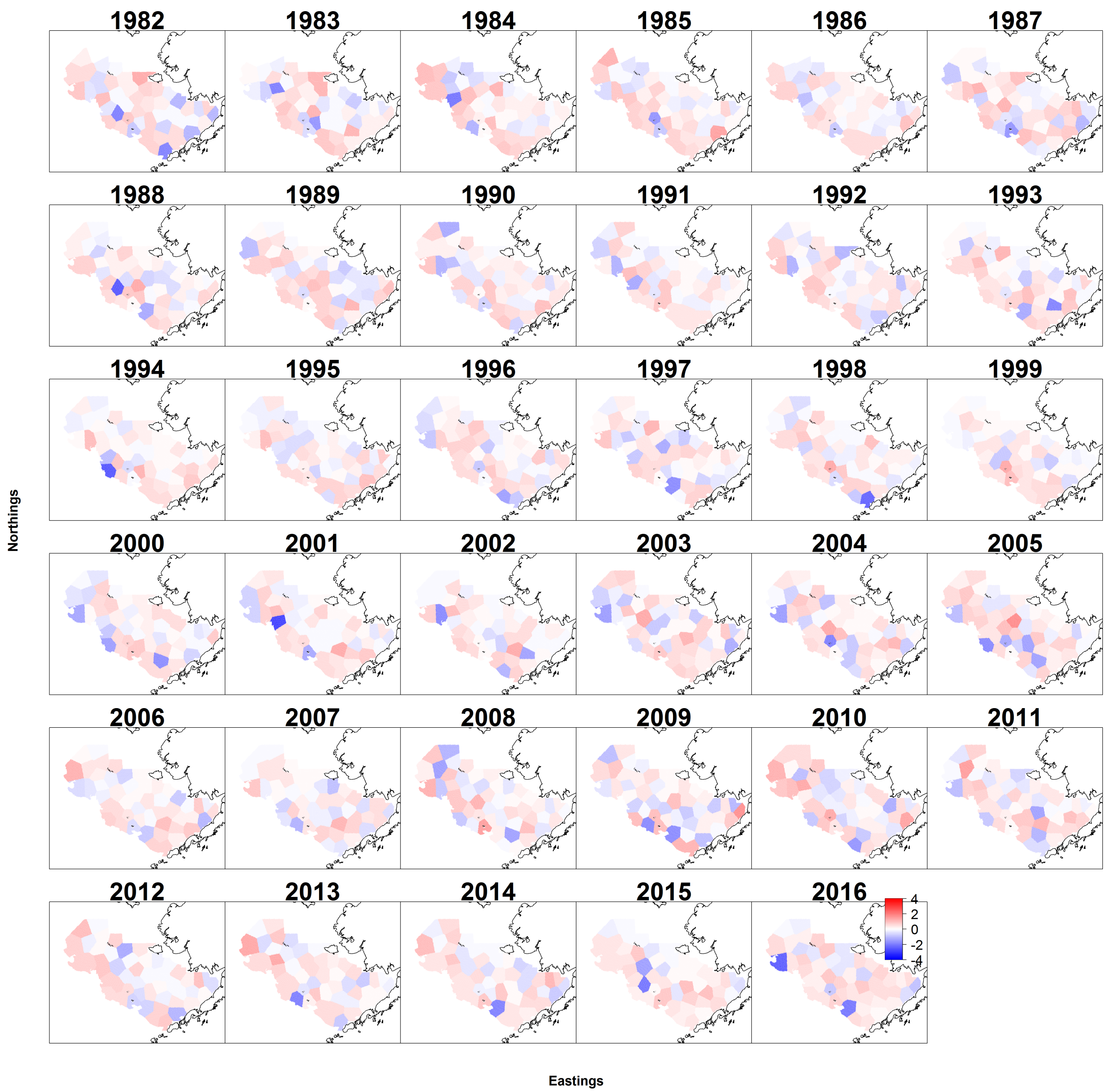

Figure 5: Pearson residuals for encounter-probability by knot

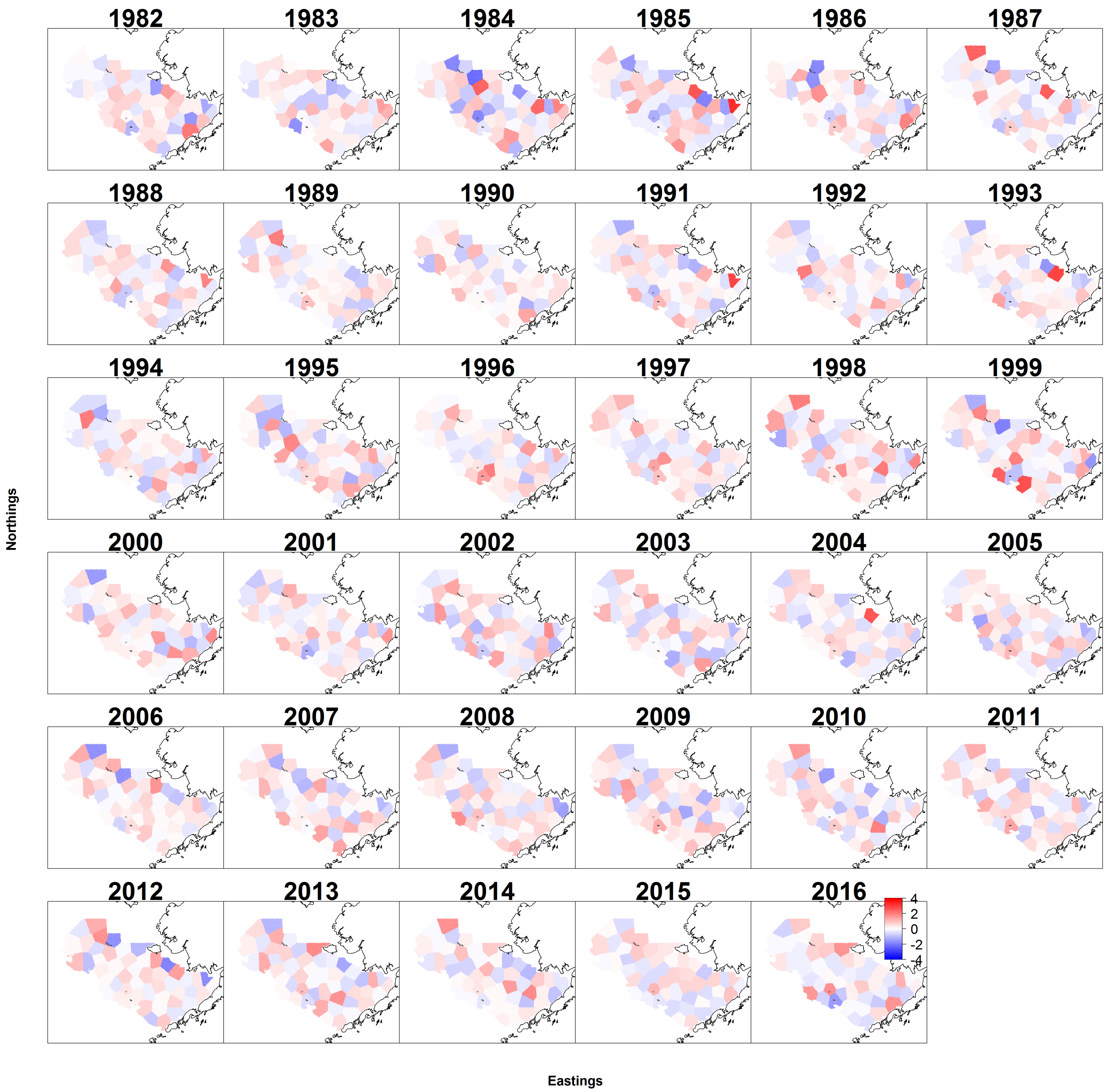

Figure 6: Pearson residuals for positive catch rates by knot

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)
```

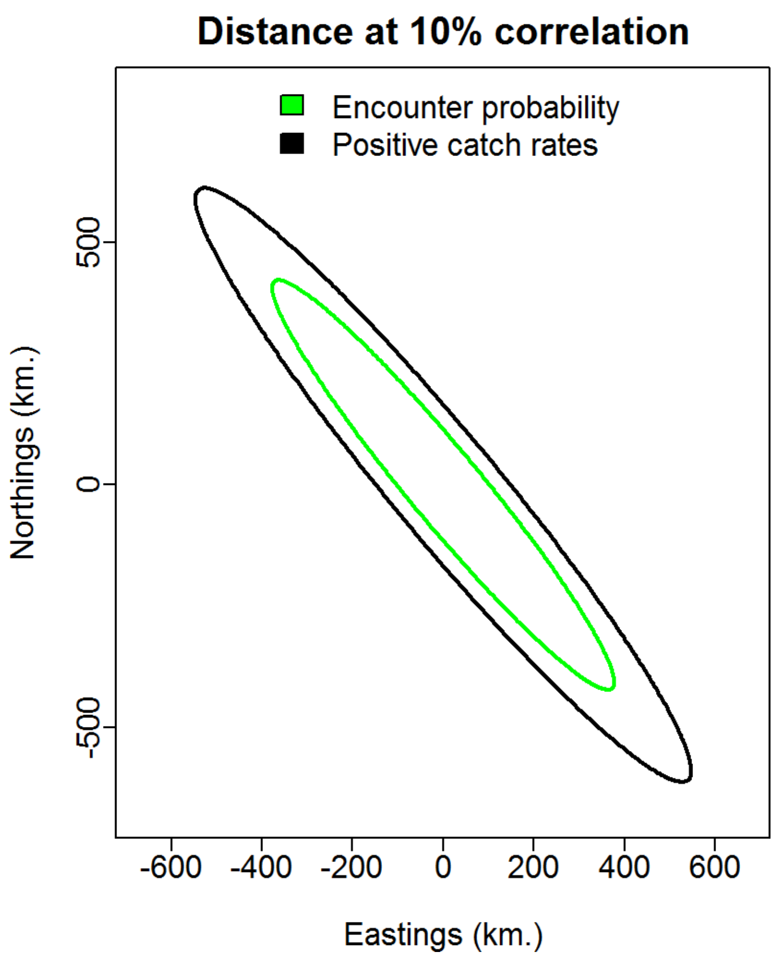

Figure 7: Decorrelation distance for different directions

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))
```

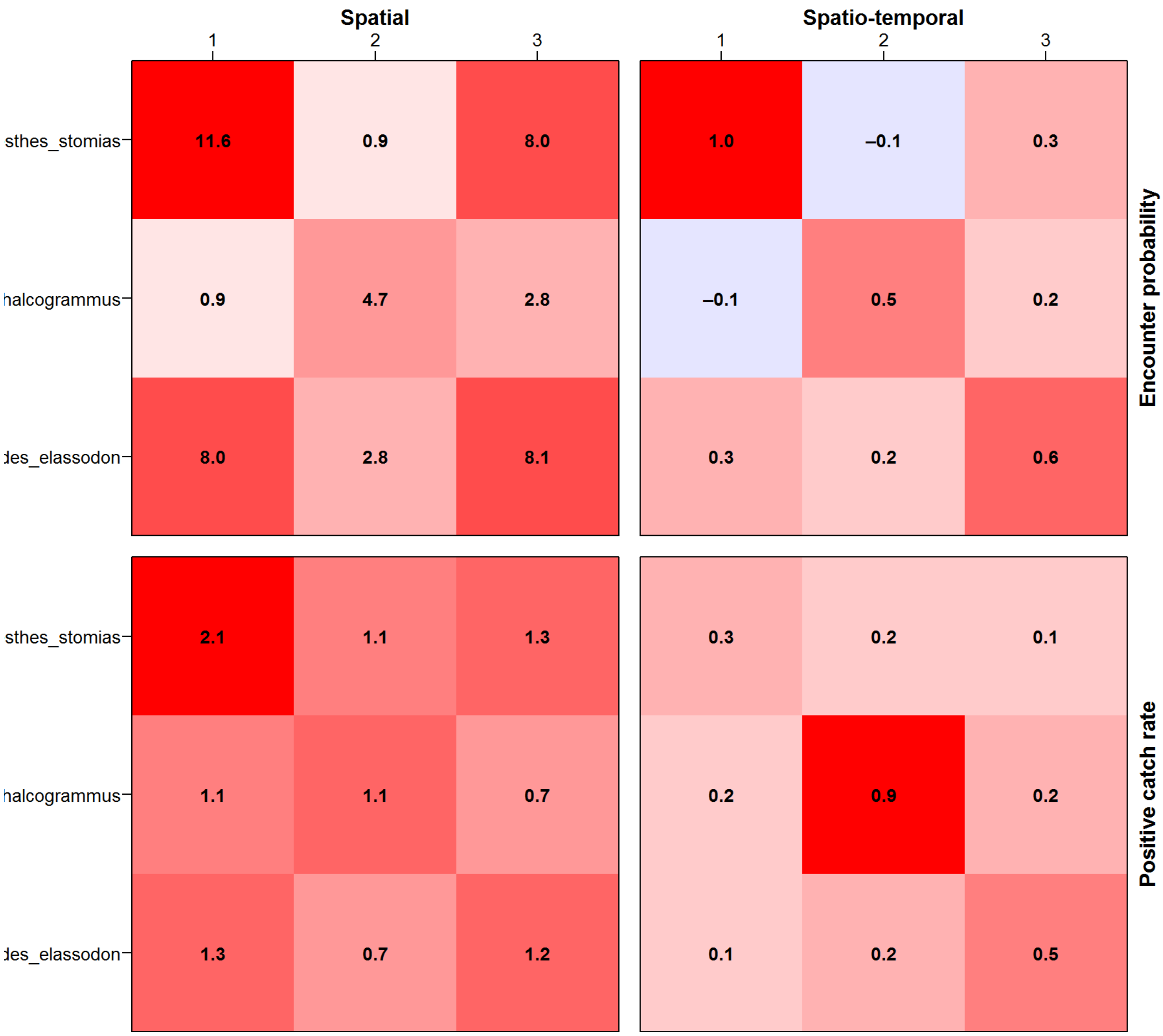

Figure 8: Spatial and spatio-temporal covariance

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"]))
```

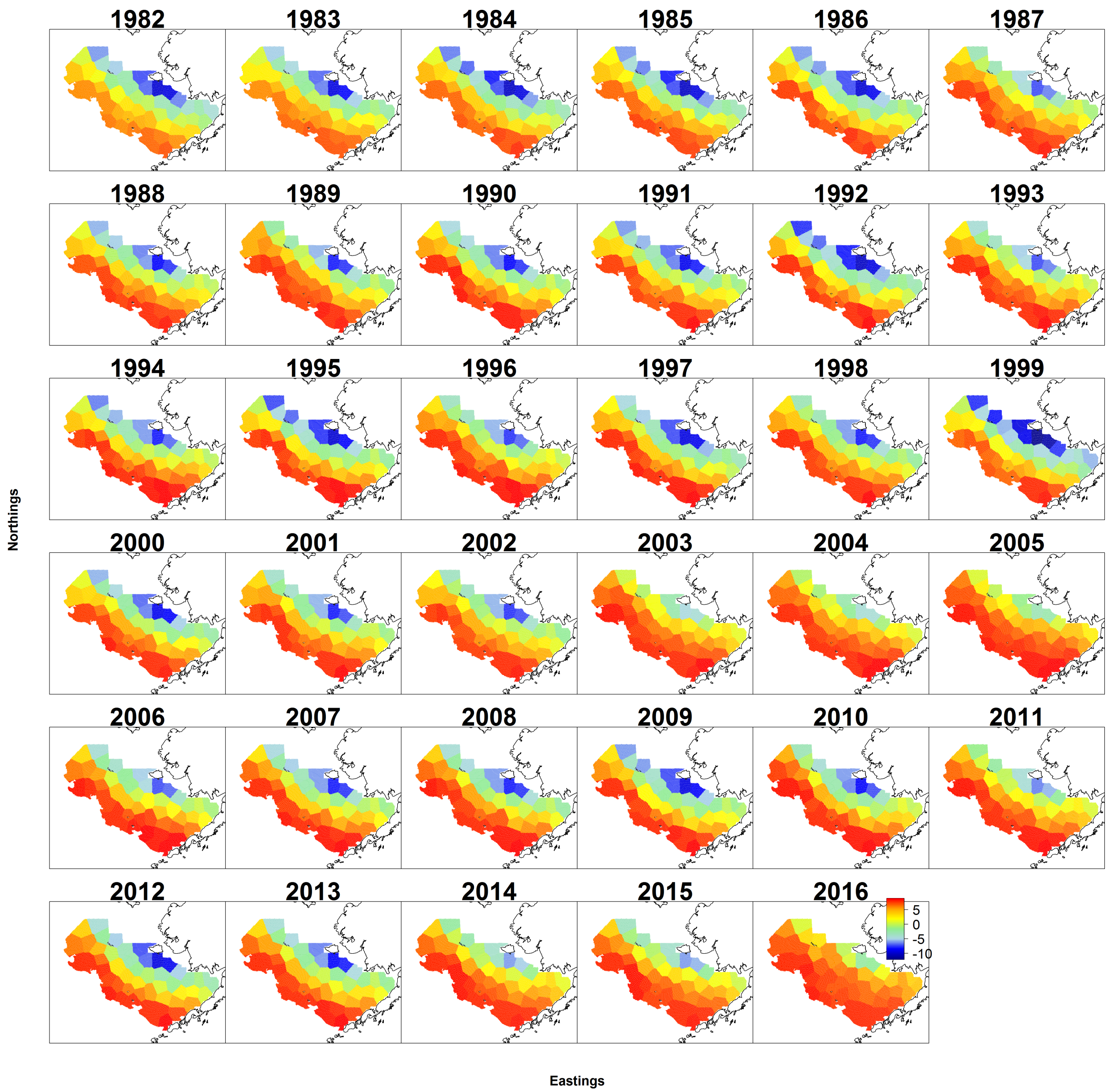

Figure 9: Density maps for each year for arrowtooth flounder

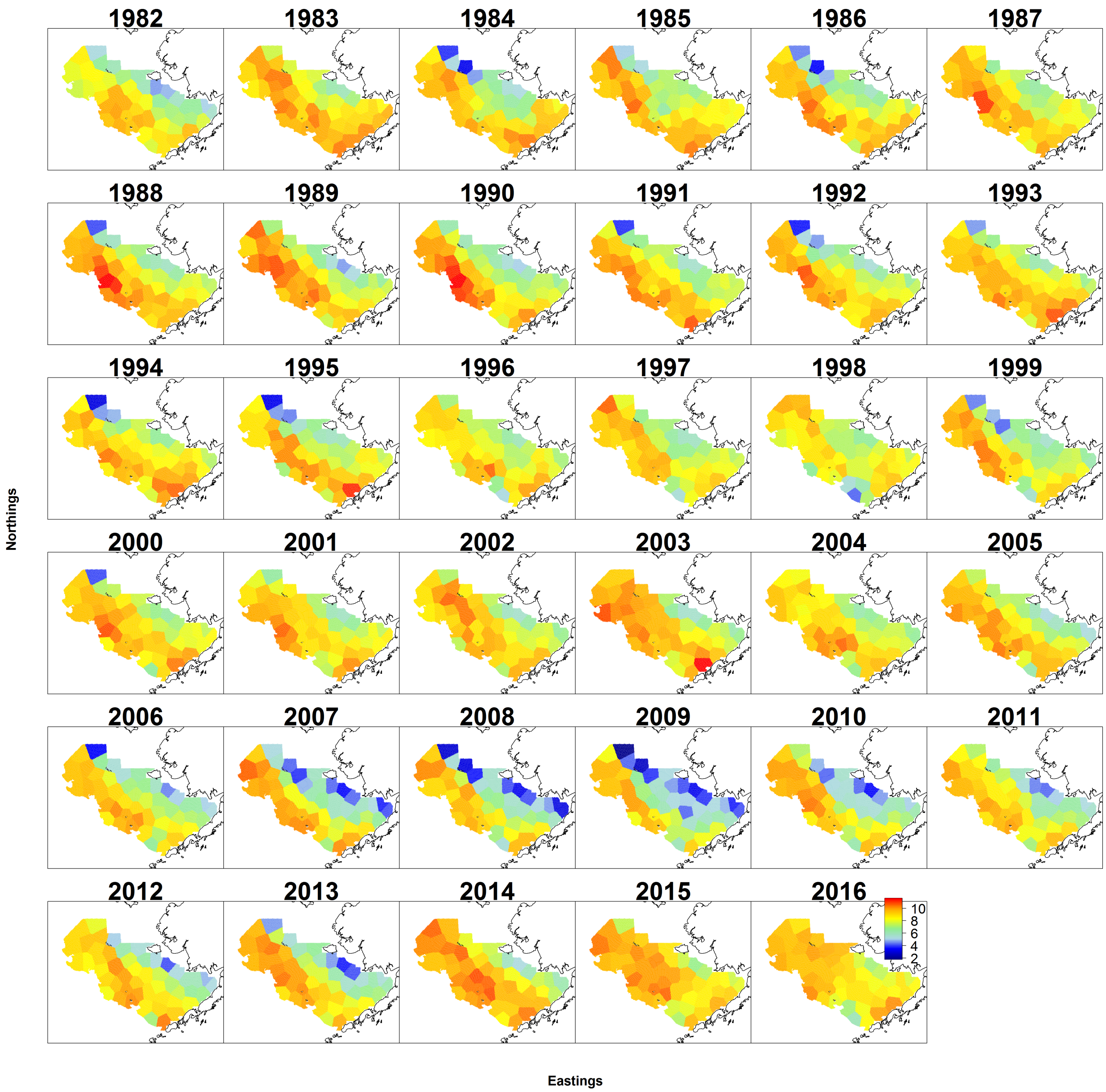

Figure 10: Density maps for each year for Alaska pollock

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	144539	14117
Atheresthes_stomias	1985	159191	15511
Atheresthes_stomias	1986	192116	18334
Atheresthes_stomias	1987	282951	25800
Atheresthes_stomias	1988	286339	26542
Atheresthes_stomias	1989	329649	28784
Atheresthes_stomias	1990	371868	34531
Atheresthes_stomias	1991	263360	26139
Atheresthes_stomias	1992	291362	30619
Atheresthes_stomias	1993	413322	36091
Atheresthes_stomias	1994	456731	44291
Atheresthes_stomias	1995	391250	40099
Atheresthes_stomias	1996	486619	44812
Atheresthes_stomias	1997	387237	36275
Atheresthes_stomias	1998	306538	27454
Atheresthes_stomias	1999	185833	19306
Atheresthes_stomias	2000	277583	25496
Atheresthes_stomias	2001	342029	30674
Atheresthes_stomias	2002	276770	24311
Atheresthes_stomias	2003	497707	40160
Atheresthes_stomias	2004	514974	42567
Atheresthes_stomias	2005	693423	55143
Atheresthes_stomias	2006	559054	48920
Atheresthes_stomias	2007	446583	40009
Atheresthes_stomias	2008	477886	42433
Atheresthes_stomias	2009	362745	33808
Atheresthes_stomias	2010	520138	46942
Atheresthes_stomias	2011	498273	42280
Atheresthes_stomias	2012	365699	33920
Atheresthes_stomias	2013	380564	34985
Atheresthes_stomias	2014	469431	39297
Atheresthes_stomias	2015	414549	34492
Atheresthes_stomias	2016	521986	39352
Gadus_chalcogrammus	1982	2443414	211827
Gadus_chalcogrammus	1983	5862955	518711
Gadus_chalcogrammus	1984	4055659	354977
Gadus_chalcogrammus	1985	4608453	449560
Gadus_chalcogrammus	1986	4432981	401043

Category	Year	Estimate_metric_tons	SD_mt
Gadus_chalcogrammus	1987	4903658	455183
Gadus_chalcogrammus	1988	6549132	643656
Gadus_chalcogrammus	1989	5908842	517502
Gadus_chalcogrammus	1990	6551129	729068
Gadus_chalcogrammus	1991	4693388	420686
Gadus_chalcogrammus	1992	4243909	393317
Gadus_chalcogrammus	1993	5053480	412702
Gadus_chalcogrammus	1994	4564148	387785
Gadus_chalcogrammus	1995	4372423	393452
Gadus_chalcogrammus	1996	2800735	220331
Gadus_chalcogrammus	1997	3351562	292777
Gadus_chalcogrammus	1998	2449507	204357
Gadus_chalcogrammus	1999	3419444	334999
Gadus_chalcogrammus	2000	4638395	400686
Gadus_chalcogrammus	2001	4018521	353178
Gadus_chalcogrammus	2002	4421402	347734
Gadus_chalcogrammus	2003	7416822	663535
Gadus_chalcogrammus	2004	3691169	301273
Gadus_chalcogrammus	2005	4418697	372833
Gadus_chalcogrammus	2006	2903146	260096
Gadus_chalcogrammus	2007	3956879	405950
Gadus_chalcogrammus	2008	2759964	286115
Gadus_chalcogrammus	2009	2003804	226413
Gadus_chalcogrammus	2010	3351558	336489
Gadus_chalcogrammus	2011	2933195	265809
Gadus_chalcogrammus	2012	3271431	273257
Gadus_chalcogrammus	2013	4259463	384219
Gadus_chalcogrammus	2014	7317175	570096
Gadus_chalcogrammus	2015	6333135	485375
Gadus_chalcogrammus	2016	4589904	339786
Hippoglossoides_elassodon	1982	190157	15384
Hippoglossoides_elassodon	1983	243392	18184
Hippoglossoides_elassodon	1984	253018	20489
Hippoglossoides_elassodon	1985	246102	19249
Hippoglossoides_elassodon	1986	322157	25283
Hippoglossoides_elassodon	1987	370797	29877
Hippoglossoides_elassodon	1988	504258	39500
Hippoglossoides_elassodon	1989	470716	36459
Hippoglossoides_elassodon	1990	549522	43221
Hippoglossoides_elassodon	1991	515735	41335
Hippoglossoides_elassodon	1992	567643	44681
Hippoglossoides_elassodon	1993	578248	45517
Hippoglossoides_elassodon	1994	649208	51091
Hippoglossoides_elassodon	1995	553245	44922
Hippoglossoides_elassodon	1996	575393	45093
Hippoglossoides_elassodon	1997	711445	57595
Hippoglossoides_elassodon	1998	646764	53507
Hippoglossoides_elassodon	1999	354328	28829
Hippoglossoides_elassodon	2000	364288	27771
Hippoglossoides_elassodon	2001	466218	36078
Hippoglossoides_elassodon	2002	503611	38315
Hippoglossoides_elassodon	2003	469800	35325

Category	Year	Estimate_metric_tons	SD_mt
Hippoglossoides_elassodon	2004	573278	42319
Hippoglossoides_elassodon	2005	612226	45584
Hippoglossoides_elassodon	2006	572853	42730
Hippoglossoides_elassodon	2007	548479	42900
Hippoglossoides_elassodon	2008	488288	37765
Hippoglossoides_elassodon	2009	359242	30357
Hippoglossoides_elassodon	2010	407601	32436
Hippoglossoides_elassodon	2011	510629	43116
Hippoglossoides_elassodon	2012	346192	28211
Hippoglossoides_elassodon	2013	414886	36024
Hippoglossoides_elassodon	2014	469586	36041
Hippoglossoides_elassodon	2015	369204	27642
Hippoglossoides_elassodon	2016	427500	30173

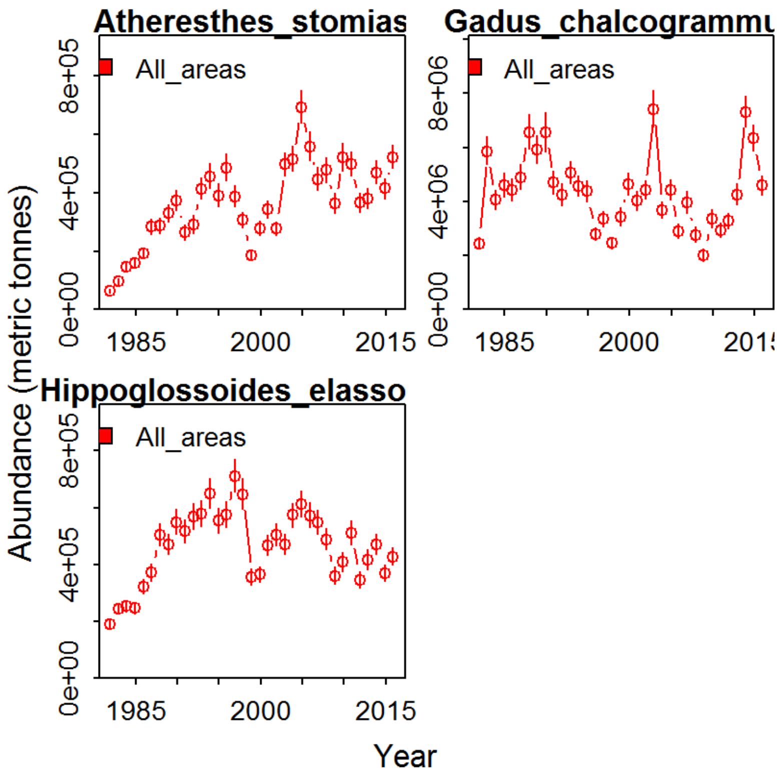

Figure 11: Index of abundance plus/minus 1 standard error

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)
```

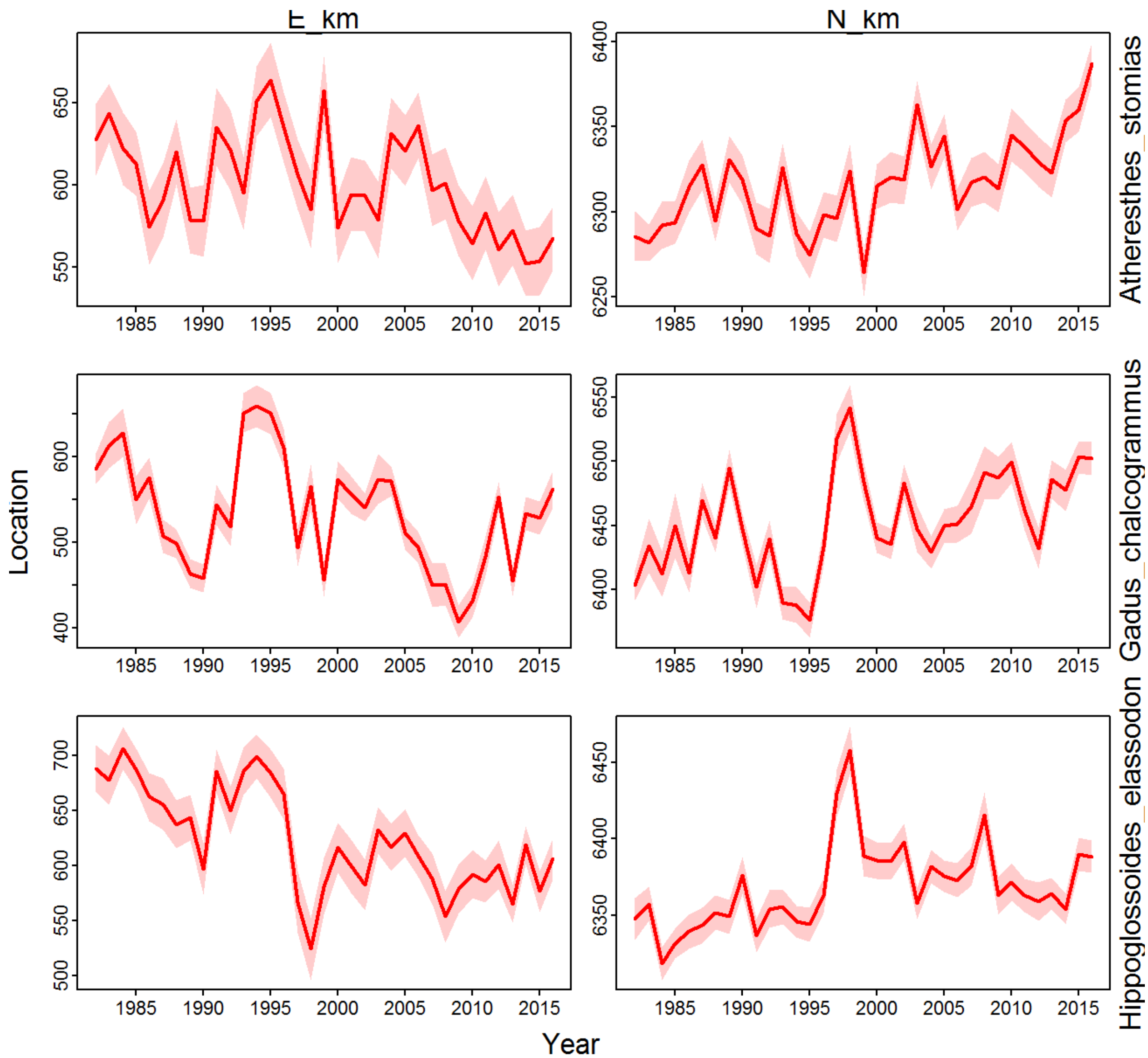

Figure 12: Center of gravity (COG) indicating shifts in distribution plus/minus 1 standard error

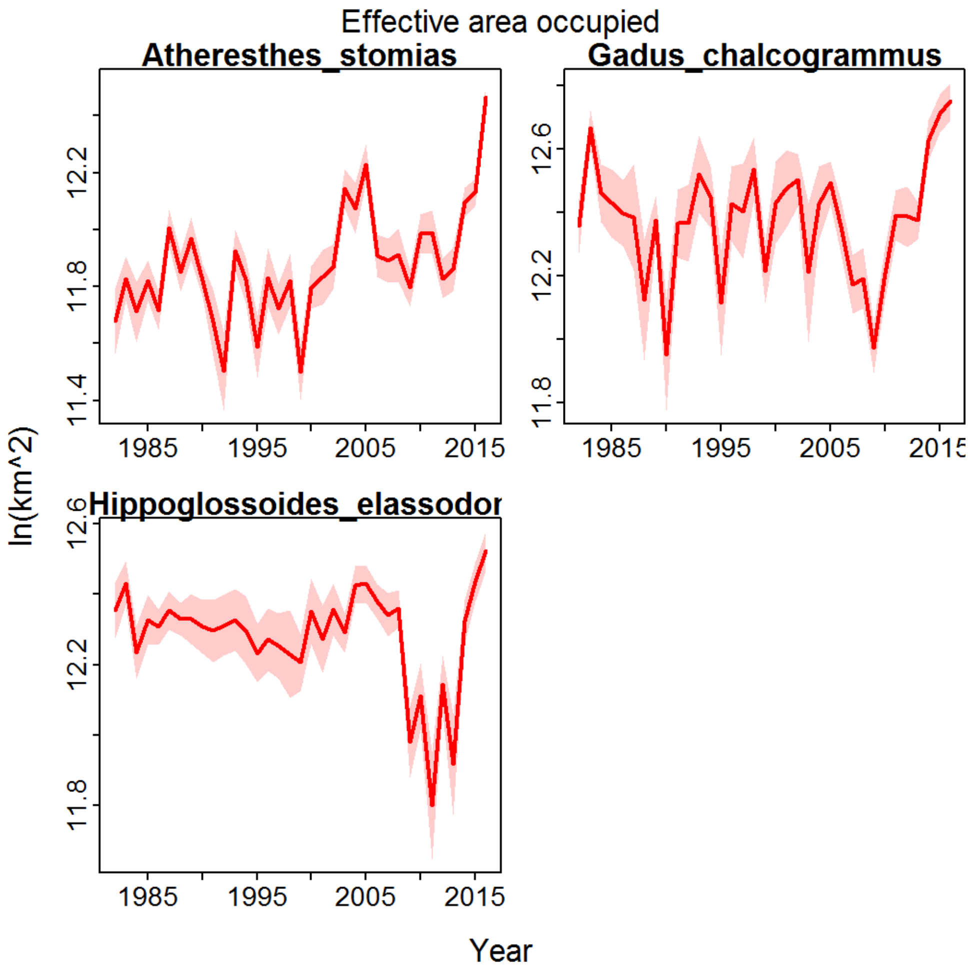

Figure 13: Effective area occupied indicating range expansion/contraction plus/minus 1 standard error

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.

```
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.

```
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)
```

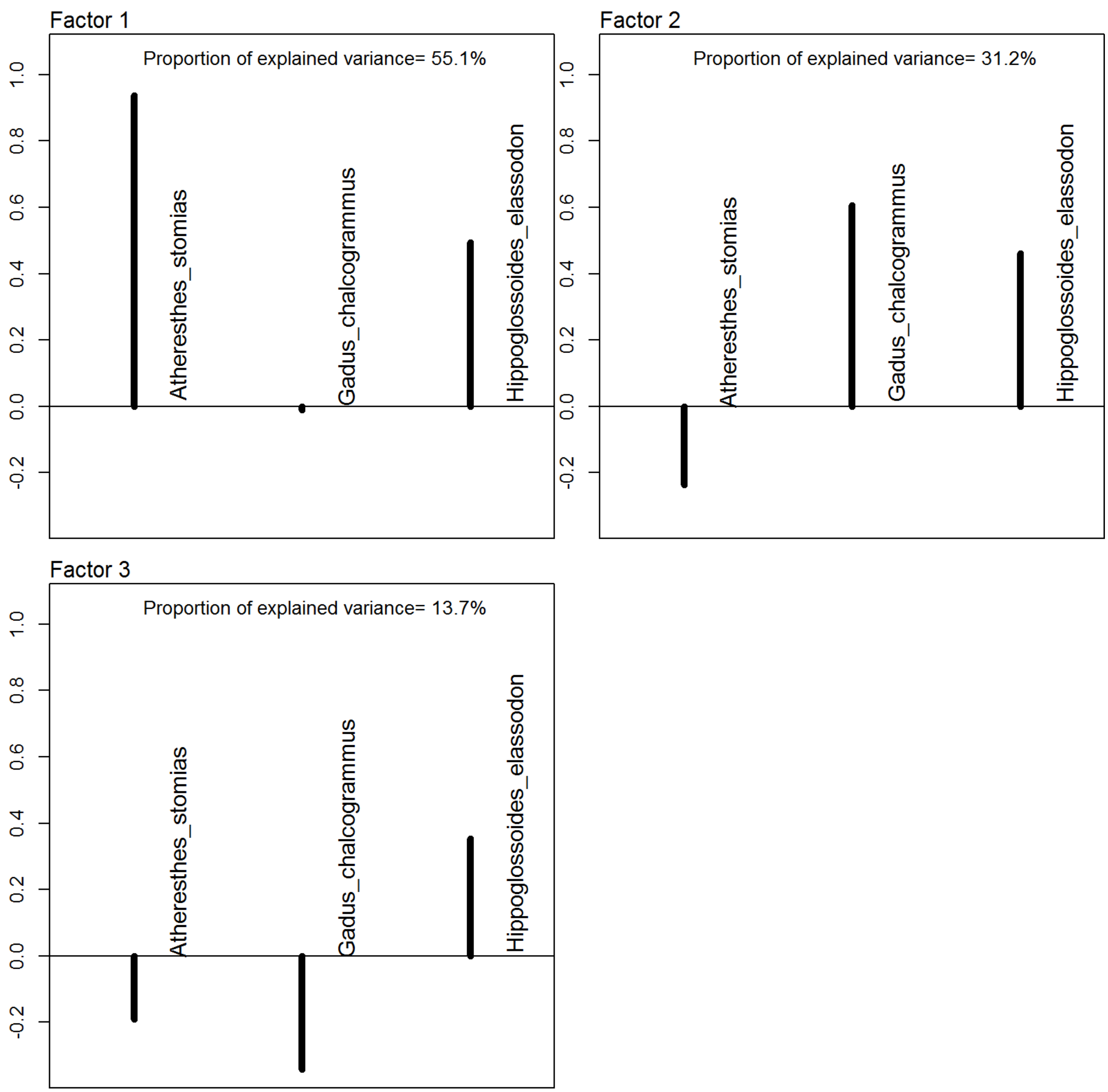

Figure 14: Factor loadings for spatio-temporal variation in encounter probability

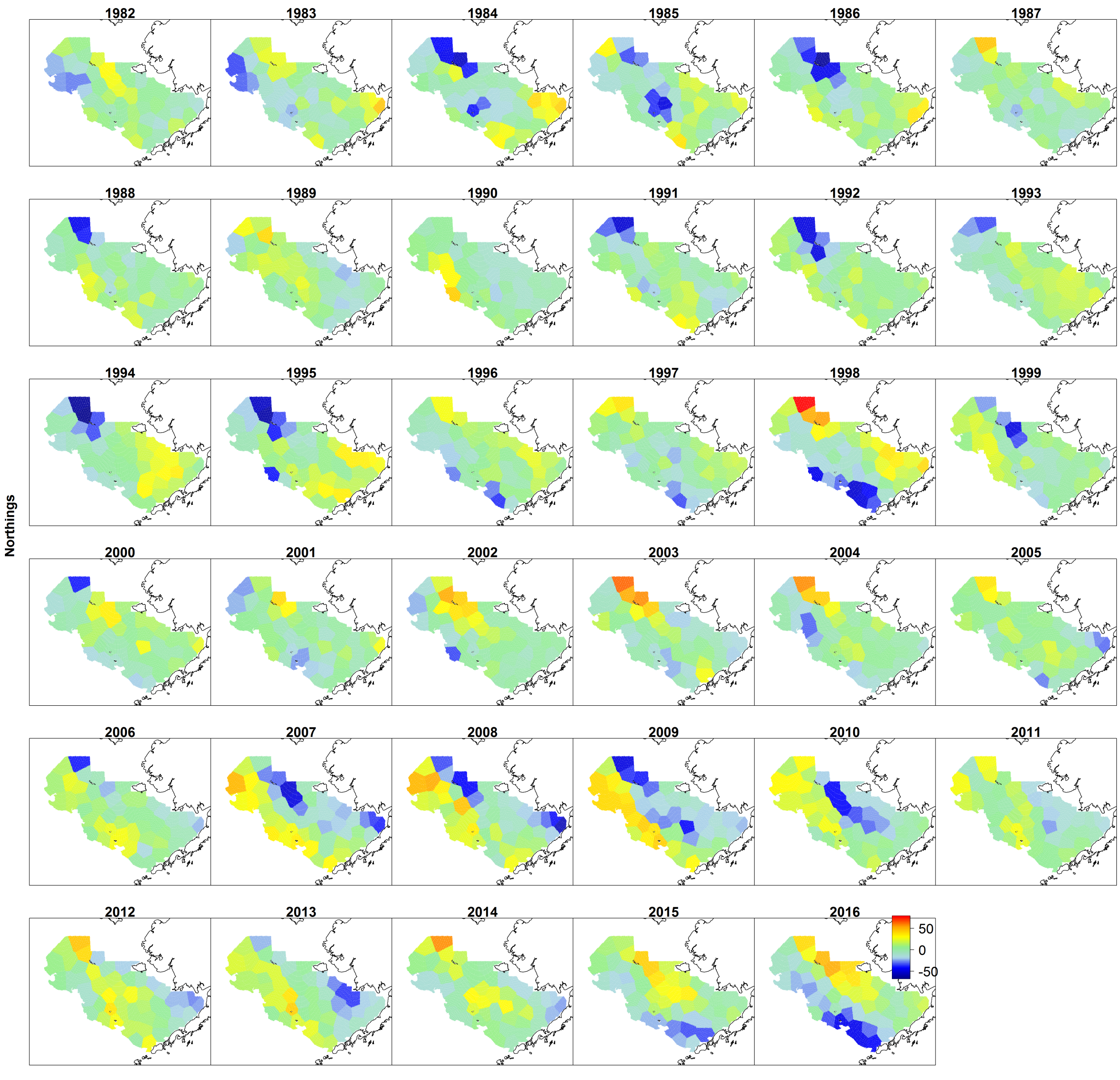

Figure 15: Factor maps for dominant (first) factor for spatio-temporal variation in positive catch rates