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

James Thorson

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Contents

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

First, we install VAST. We also have to install TMB as appropriate for the operating system (see directions elsewhere).

```
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., `?PlotIndex_Fn`.

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 packages.

3 Settings

We use latest version for CPP code

```
Version = "VAST_v1_9_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")[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 = ThorsonUtilities::bundlelist(c("Version",
    "Method", "grid_size_km", "n_x", "FieldConfig",
    "RhoConfig", "OverdispersionConfig", "ObsModel",
    "Kmeans_Config", "Region", "Species_set", "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…

Table 1: Table continues below

spp	Year	Catch_KG	AreaSwept_km2	Vessel
Atheresthes_stomias	1982	6.98	0.01	0

spp	Year	Catch_KG	AreaSwept_km2	Vessel
Atheresthes_stomias	1982	4.37	0.01	0
Atheresthes_stomias	1982	12.6	0.01	0
Atheresthes_stomias	1982	4.28	0.01	0
Atheresthes_stomias	1982	0	0.01	0
Atheresthes_stomias	1982	10.3	0.01	0

Lat	Lon
55	-167
55	-166
55	-166
55	-165
55	-165
55.3	-167

... and tail The data is formatted as shown here, with head...

Table 3: Table continues below

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

	AreaSwept_km2	Vessel	Lat	Lon
38878	0.01	0	61.7	-176
38879	0.01	0	62	-174
38880	0.01	0	62	-174
38881	0.01	0	62	-175
38882	0.01	0	62	-176
38883	0.01	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, Spatial_List$loc_UTM,
    knot_i = Spatial_List$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)
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)
```

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	-0.0007543
ln_H_input	-50	-1.154	50	7.985e-05
beta1_ct	-50	-1.256	50	-2.753e-05
beta1_ct	-50	3.847	50	-9.413e-05
beta1_ct	-50	3.088	50	-3.152e-05
beta1_ct	-50	-0.8955	50	-7.529e-05
beta1_ct	-50	3.842	50	-0.0001589
beta1_ct	-50	3.443	50	3.786e-05
beta1_ct	-50	-1.399	50	-2.481e-05
beta1_ct	-50	3.895	50	-0.0001332
beta1_ct	-50	2.833	50	3.358e-05
beta1_ct	-50	-1.464	50	6.852e-06
beta1_ct	-50	4.54	50	9.567e-05
beta1_ct	-50	2.843	50	-3.378e-05
beta1_ct	-50	-1.277	50	-5.331e-05
beta1_ct	-50	4.896	50	-9.381e-05
beta1_ct	-50	2.457	50	0.000217
beta1_ct	-50	0.2562	50	-0.000119
beta1_ct	-50	3.699	50	-0.0006076

Param	Lower	MLE	Upper	final_gradient
beta1_ct	-50	2.442	50	0.0002296
beta1_ct	-50	-0.5266	50	0.0001987
beta1_ct	-50	4.554	50	0.0003459
beta1_ct	-50	2.077	50	-0.0003794
beta1_ct	-50	0.3133	50	0.0001357
beta1_ct	-50	3.694	50	-6.657e-05
beta1_ct	-50	2.588	50	-0.0003571
beta1_ct	-50	-0.7503	50	8.354e-05
beta1_ct	-50	3.89	50	-0.0002452
beta1_ct	-50	2.846	50	-0.0002654
beta1_ct	-50	-1.036	50	5.894e-05
beta1_ct	-50	5.499	50	0.0001019
beta1_ct	-50	2.747	50	-4.82e-05
beta1_ct	-50	-2.359	50	3.425e-05
beta1_ct	-50	4.066	50	1.546e-05
beta1_ct	-50	3.018	50	-1.854e-05
beta1_ct	-50	0.05987	50	-8.814e-05
beta1_ct	-50	4.744	50	-3.469e-05
beta1_ct	-50	3.203	50	0.0002571
beta1_ct	-50	-1.514	50	2.658e-05
beta1_ct	-50	5.166	50	7.789e-05
beta1_ct	-50	2.976	50	-0.0001274
beta1_ct	-50	-2.512	50	9.763e-05
beta1_ct	-50	4.392	50	0.0002008
beta1_ct	-50	2.425	50	-0.0002122
beta1_ct	-50	-0.5555	50	-7.446e-05
beta1_ct	-50	4.644	50	1.898e-05
beta1_ct	-50	3.08	50	0.0001678
beta1_ct	-50	-1.831	50	-0.0001046
beta1_ct	-50	4.309	50	-3.358e-05
beta1_ct	-50	3.285	50	0.0001531
beta1_ct	-50	-0.6577	50	4.597e-05
beta1_ct	-50	4.576	50	2.659e-05
beta1_ct	-50	4.611	50	-6.192e-05
beta1_ct	-50	-3.12	50	-2.407e-05
beta1_ct	-50	5.698	50	1.188e-06
beta1_ct	-50	1.881	50	-0.0001226
beta1_ct	-50	-1.363	50	-2.483e-05
beta1_ct	-50	4.671	50	2.738e-05
beta1_ct	-50	2.711	50	1.392e-05
beta1_ct	-50	-0.3359	50	-0.0001154
beta1_ct	-50	5.225	50	-5.011e-05
beta1_ct	-50	3.141	50	0.0002166
beta1_ct	-50	0.1005	50	4.898e-05
beta1_ct	-50	4.328	50	6.378e-06
beta1_ct	-50	2.858	50	-5.053e-05
beta1_ct	-50	2.384	50	0.0001305
beta1_ct	-50	4.118	50	0.0002172
beta1_ct	-50	2.889	50	-0.0001529
beta1_ct	-50	1.846	50	5.41e-05
beta1_ct	-50	4.999	50	0.000106
beta1_ct	-50	2.758	50	-0.0001893

Param	Lower	MLE	Upper	final_gradient
beta1_ct	-50	3.082	50	-0.0001763
beta1_ct	-50	4.291	50	-0.000325
beta1_ct	-50	3.163	50	0.0004413
beta1_ct	-50	-0.00496	50	-6.367e-05
beta1_ct	-50	4.128	50	-3.2e-06
beta1_ct	-50	2.135	50	0.0001768
beta1_ct	-50	-0.5614	50	7.183e-05
beta1_ct	-50	3.75	50	-2.47e-05
beta1_ct	-50	2.331	50	-0.0002041
beta1_ct	-50	-0.4672	50	-1.096e-05
beta1_ct	-50	2.55	50	0.000306
beta1_ct	-50	2.099	50	0.0002267
beta1_ct	-50	-1.429	50	0.000166
beta1_ct	-50	3.045	50	0.0002725
beta1_ct	-50	1.443	50	-0.0001757
beta1_ct	-50	-0.8586	50	0.0001076
beta1_ct	-50	2.642	50	3.443e-06
beta1_ct	-50	2.099	50	-0.0002842
beta1_ct	-50	1.079	50	-8.178e-05
beta1_ct	-50	4.284	50	-4.905e-05
beta1_ct	-50	2.316	50	0.0001983
beta1_ct	-50	-1.732	50	-8.272e-06
beta1_ct	-50	4.237	50	0.000196
beta1_ct	-50	1.725	50	-2.494e-05
beta1_ct	-50	-1.051	50	0.0001143
beta1_ct	-50	4.7	50	0.0001116
beta1_ct	-50	2.166	50	-0.0002467
beta1_ct	-50	1.023	50	5.503e-06
beta1_ct	-50	5.749	50	-2.644e-07
beta1_ct	-50	2.391	50	7.019e-05
beta1_ct	-50	0.7603	50	1.399e-07
beta1_ct	-50	6.856	50	-9.778e-06
beta1_ct	-50	2.351	50	6.457e-05
beta1_ct	-50	3.608	50	-0.0001972
beta1_ct	-50	5.685	50	-5.949e-05
beta1_ct	-50	3.241	50	0.0002916
L_omega1_z	-50	3.405	50	0.000102
L_omega1_z	-50	0.268	50	-0.000118
L_omega1_z	-50	2.16	50	-0.0004432
L_omega1_z	-50	2.358	50	4.35e-05
L_omega1_z	-50	0.9882	50	-4.523e-05
L_omega1_z	-50	1.268	50	-0.0003386
L_epsilon1_z	-50	0.9849	50	-0.001842
L_epsilon1_z	-50	-0.08926	50	3.37e-05
L_epsilon1_z	-50	0.6911	50	-0.002213
L_epsilon1_z	-50	0.291	50	0.0005548
L_epsilon1_z	-50	0.2593	50	-0.001682
L_epsilon1_z	-50	-0.6556	50	0.001858
logkappa1	-5.978	-4.669	-3.114	-8.313e-05
beta2_ct	-50	3.375	50	0.000498
beta2_ct	-50	7.688	50	0.0003862
beta2_ct	-50	5.564	50	-0.0004727

Param	Lower	MLE	Upper	final_gradient
beta2_ct	-50	3.951	50	-0.0002927
beta2_ct	-50	8.968	50	6.829e-05
beta2_ct	-50	5.757	50	-5.973e-05
beta2_ct	-50	4.083	50	0.0009446
beta2_ct	-50	8.212	50	-0.0003181
beta2_ct	-50	5.511	50	0.0008057
beta2_ct	-50	4.359	50	-0.0006713
beta2_ct	-50	8.498	50	-0.0002622
beta2_ct	-50	5.538	50	0.0008543
beta2_ct	-50	4.103	50	-0.000934
beta2_ct	-50	8.221	50	0.0004917
beta2_ct	-50	5.642	50	-0.0001959
beta2_ct	-50	5.086	50	-7.592e-05
beta2_ct	-50	8.617	50	1.737e-05
beta2_ct	-50	5.993	50	-0.0001648
beta2_ct	-50	4.755	50	0.0003827
beta2_ct	-50	8.528	50	-0.0001007
beta2_ct	-50	6.14	50	3.601e-06
beta2_ct	-50	5.004	50	0.000239
beta2_ct	-50	8.426	50	-0.0001671
beta2_ct	-50	6.062	50	0.0005161
beta2_ct	-50	4.951	50	-0.0007018
beta2_ct	-50	8.335	50	0.0001121
beta2_ct	-50	6.232	50	0.0003267
beta2_ct	-50	4.496	50	0.0003153
beta2_ct	-50	8.387	50	-1.206e-05
beta2_ct	-50	6.195	50	-0.0002665
beta2_ct	-50	4.685	50	8.859e-05
beta2_ct	-50	8.173	50	-0.000142
beta2_ct	-50	6.177	50	0.0003029
beta2_ct	-50	5.38	50	0.0003981
beta2_ct	-50	8.537	50	-0.0001962
beta2_ct	-50	6.325	50	3.124e-05
beta2_ct	-50	5.522	50	0.0003625
beta2_ct	-50	8.303	50	9.266e-06
beta2_ct	-50	6.319	50	-0.0003787
beta2_ct	-50	5.185	50	-0.000403
beta2_ct	-50	7.958	50	0.0002547
beta2_ct	-50	6.053	50	-9.961e-05
beta2_ct	-50	5.618	50	6.355e-05
beta2_ct	-50	8.008	50	0.0001509
beta2_ct	-50	6.273	50	-0.0004562
beta2_ct	-50	5.094	50	-9.062e-05
beta2_ct	-50	8.13	50	-0.0002499
beta2_ct	-50	6.4	50	0.0002934
beta2_ct	-50	5.083	50	-0.0002081
beta2_ct	-50	7.862	50	-9.524e-06
beta2_ct	-50	6.375	50	-0.0002815
beta2_ct	-50	4.219	50	-0.0002513
beta2_ct	-50	7.763	50	0.0002138
beta2_ct	-50	5.521	50	-5.724e-05
beta2_ct	-50	4.899	50	0.001032

Param	Lower	MLE	Upper	final_gradient
beta2_ct	-50	8.403	50	0.0001149
beta2_ct	-50	5.9	50	-0.001014
beta2_ct	-50	5.045	50	0.0001402
beta2_ct	-50	8.479	50	-0.0003318
beta2_ct	-50	6.044	50	0.0001396
beta2_ct	-50	4.722	50	-0.0001922
beta2_ct	-50	8.307	50	2.868e-05
beta2_ct	-50	6.16	50	-0.0002695
beta2_ct	-50	5.621	50	1.531e-05
beta2_ct	-50	8.844	50	2.218e-05
beta2_ct	-50	6.061	50	0.000159
beta2_ct	-50	5.755	50	-7.925e-05
beta2_ct	-50	8.348	50	5.524e-05
beta2_ct	-50	6.33	50	-0.0001293
beta2_ct	-50	6.126	50	-1.14e-05
beta2_ct	-50	8.205	50	0.0001193
beta2_ct	-50	6.328	50	3.561e-05
beta2_ct	-50	5.382	50	-0.0001685
beta2_ct	-50	7.537	50	0.00018
beta2_ct	-50	6.052	50	-0.0001973
beta2_ct	-50	5.031	50	-2.672e-05
beta2_ct	-50	7.382	50	1.738e-05
beta2_ct	-50	5.984	50	0.0003414
beta2_ct	-50	5.28	50	-0.0007029
beta2_ct	-50	7.04	50	0.0002038
beta2_ct	-50	5.734	50	-0.0002133
beta2_ct	-50	4.73	50	-0.0003526
beta2_ct	-50	6.569	50	0.0003887
beta2_ct	-50	5.223	50	-0.0002289
beta2_ct	-50	5.576	50	-0.0004949
beta2_ct	-50	7.547	50	-0.0001395
beta2_ct	-50	5.529	50	0.0003683
beta2_ct	-50	5.459	50	-0.0002903
beta2_ct	-50	7.672	50	0.000257
beta2_ct	-50	5.711	50	-0.0003847
beta2_ct	-50	5.127	50	0.0001447
beta2_ct	-50	7.666	50	-0.0004564
beta2_ct	-50	5.537	50	0.0005339
beta2_ct	-50	5.178	50	0.0008376
beta2_ct	-50	7.772	50	-0.0001357
beta2_ct	-50	5.654	50	-0.0002031
beta2_ct	-50	5.737	50	-8.474e-06
beta2_ct	-50	8.766	50	-0.0001314
beta2_ct	-50	5.852	50	7.809e-05
beta2_ct	-50	5.583	50	3.145e-05
beta2_ct	-50	8.959	50	-0.0002169
beta2_ct	-50	5.887	50	0.0001031
beta2_ct	-50	6.344	50	0.0002194
beta2_ct	-50	8.877	50	-6.38e-05
beta2_ct	-50	6.1	50	0.0003164
L_omega2_z	-50	-1.444	50	-6.281e-05
L_omega2_z	-50	-0.7518	50	-0.0003621

Param	Lower	MLE	Upper	final_gradient
L_omega2_z	-50	-0.7636	50	-0.0006386
L_omega2_z	-50	-0.8668	50	0.0008099
L_omega2_z	-50	-0.0652	50	-0.00165
L_omega2_z	-50	0.6738	50	0.001333
L_epsilon2_z	-50	-0.5415	50	-0.001627
L_epsilon2_z	-50	-0.2826	50	0.002274
L_epsilon2_z	-50	-0.9256	50	-0.002069
L_epsilon2_z	-50	-0.248	50	0.0007736
L_epsilon2_z	-50	-0.1679	50	-0.005356
L_epsilon2_z	-50	-0.6256	50	0.001411
logkappa2	-5.978	-4.298	-3.114	0.005094
logSigmaM	-50	-0.01824	10	0.0006178
logSigmaM	-50	0.2275	10	-0.01674
logSigmaM	-50	0.04248	10	0.009778

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)
```

6.4 Diagnostics for positive-catch-rate component

I haven't yet added the Q-Q plotting options from `SpatialDeltaGLMM` so that is missing for now.

6.5 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 useful plots by first determining which years to plot (`Years2Include`), and labels for each plotted year (`Year_Set`)

```
Year_Set = seq(min(Data_Geostat[,'Year']),max(Data_Geostat[,'Year']))
Years2Include = which( Year_Set %in% sort(unique(Data_Geostat[,'Year'])))
```

We then run a set of 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")

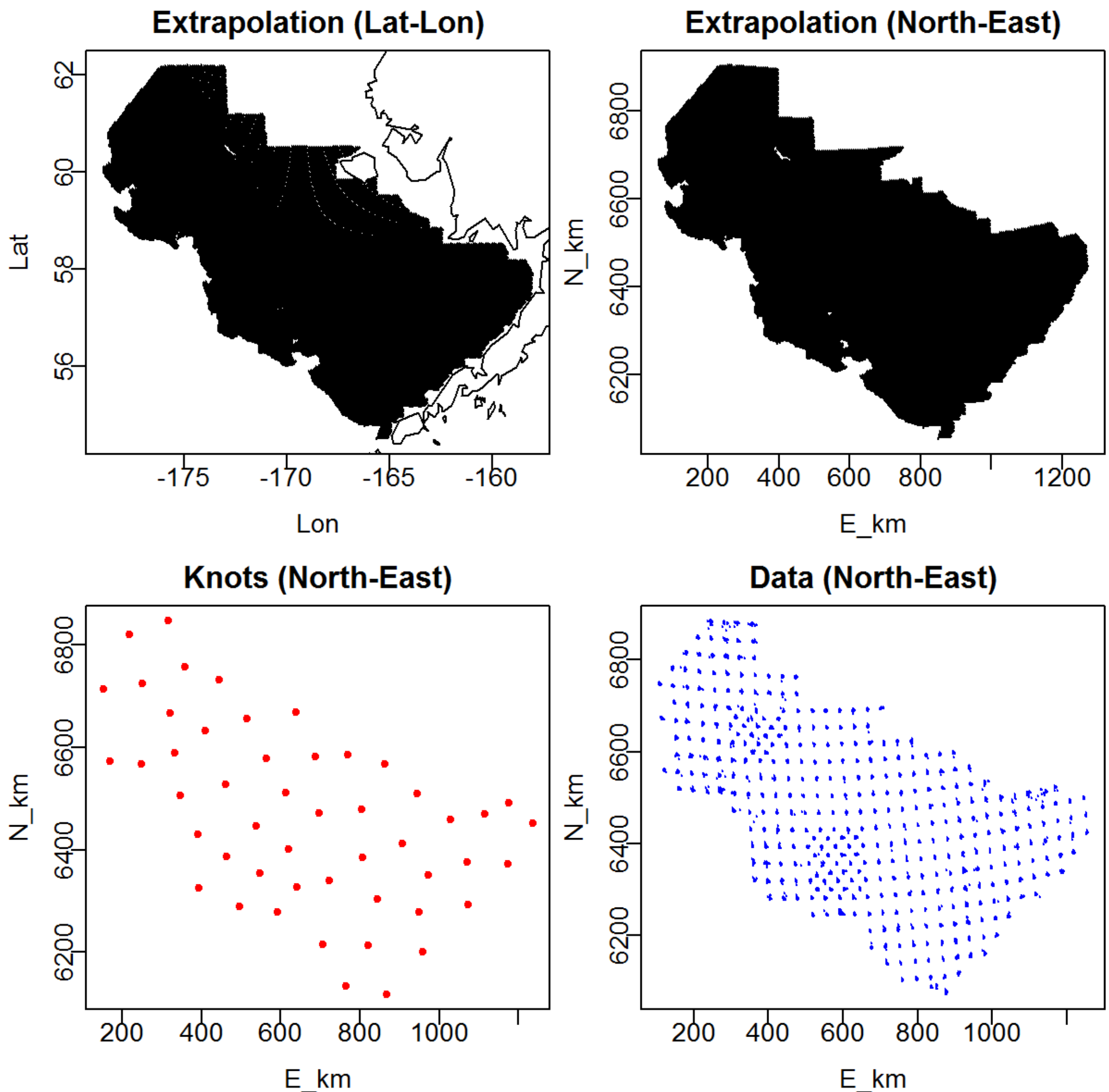

Figure 1: Spatial extent and location of knots

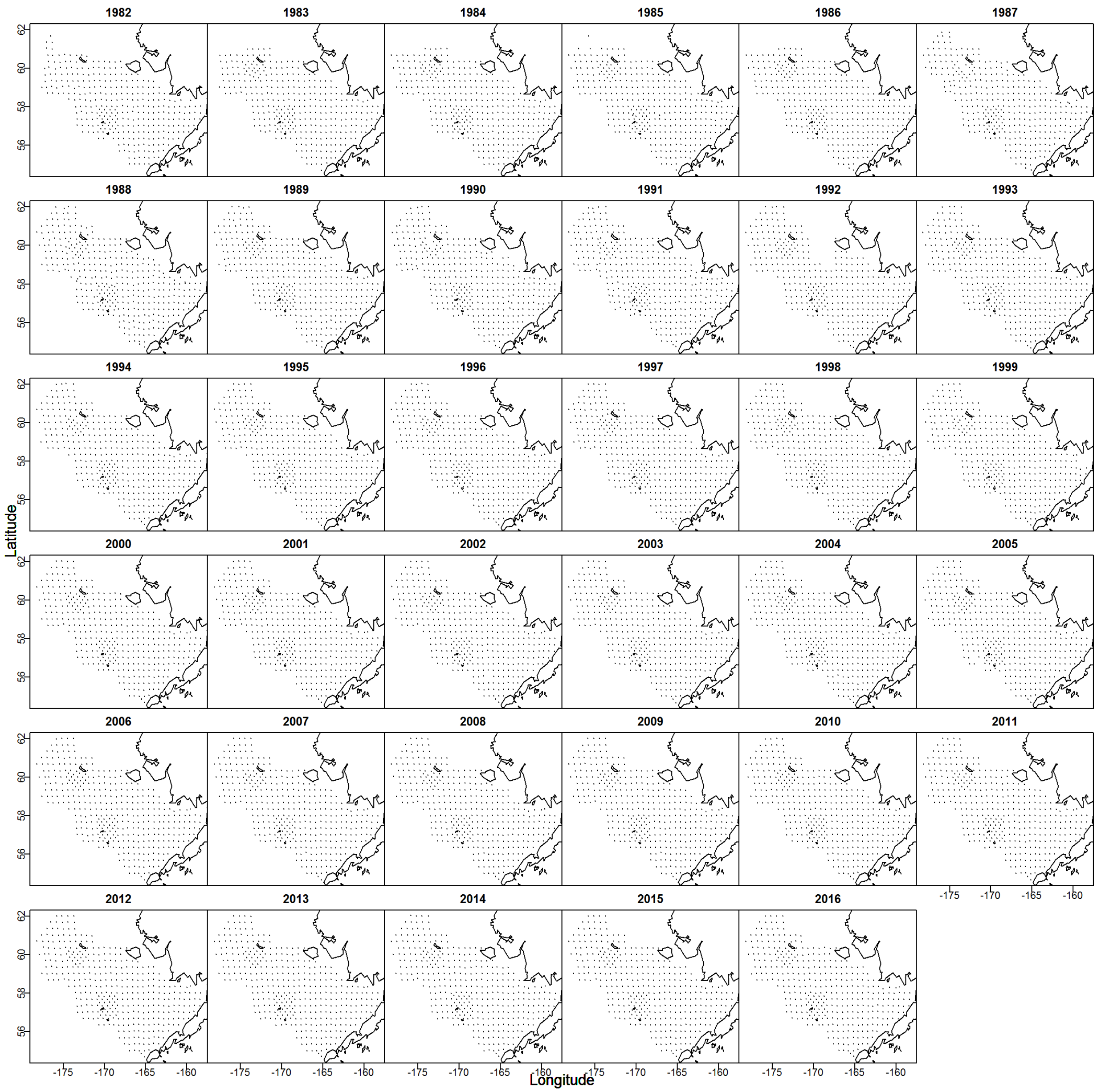

Figure 2: Spatial distribution of catch-rate data

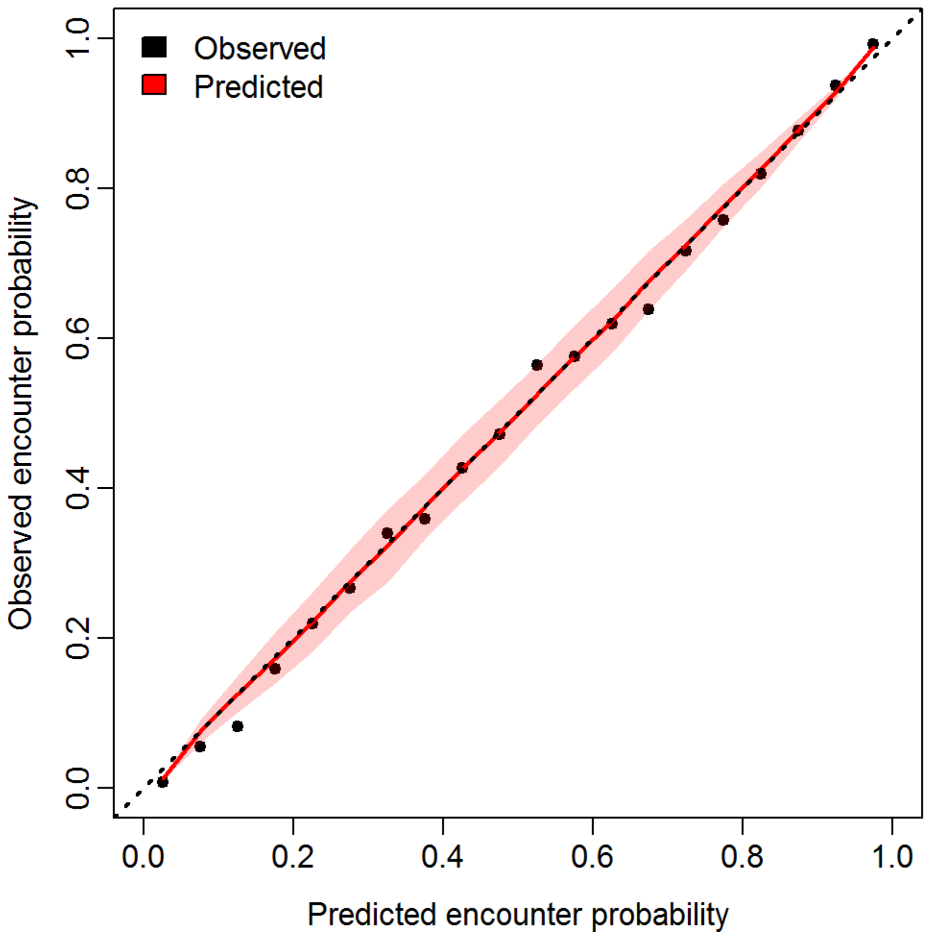

Figure 3: Expectated probability and observed frequency of encounter for “encounter probability” component

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

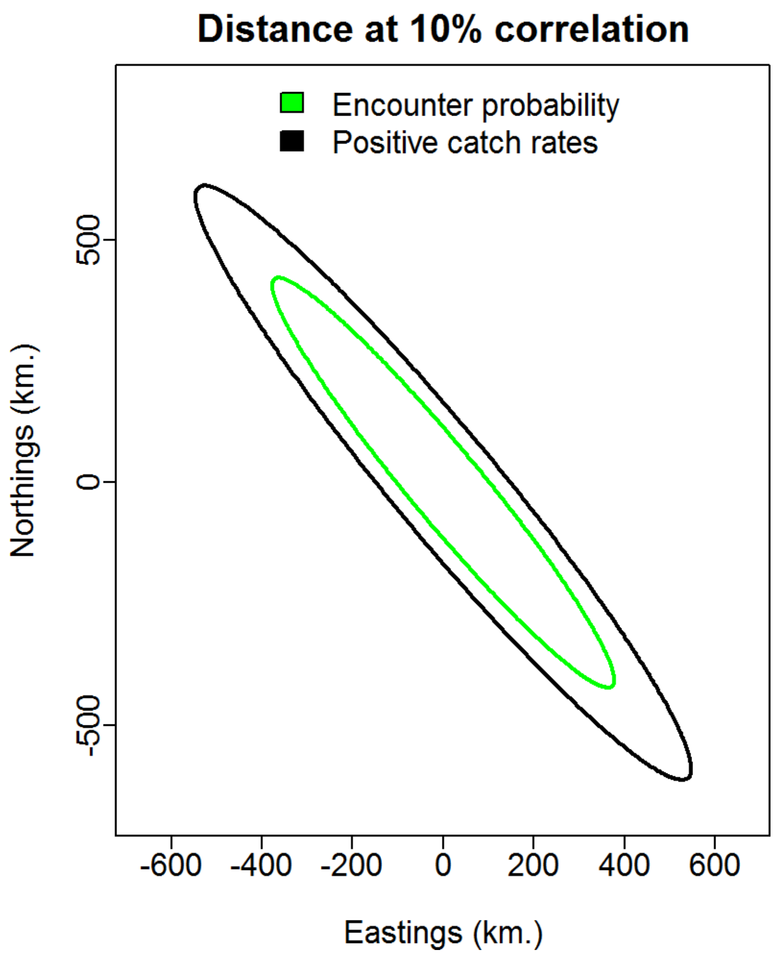

Figure 4: Decorrelation distance for different directions

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))
```

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`

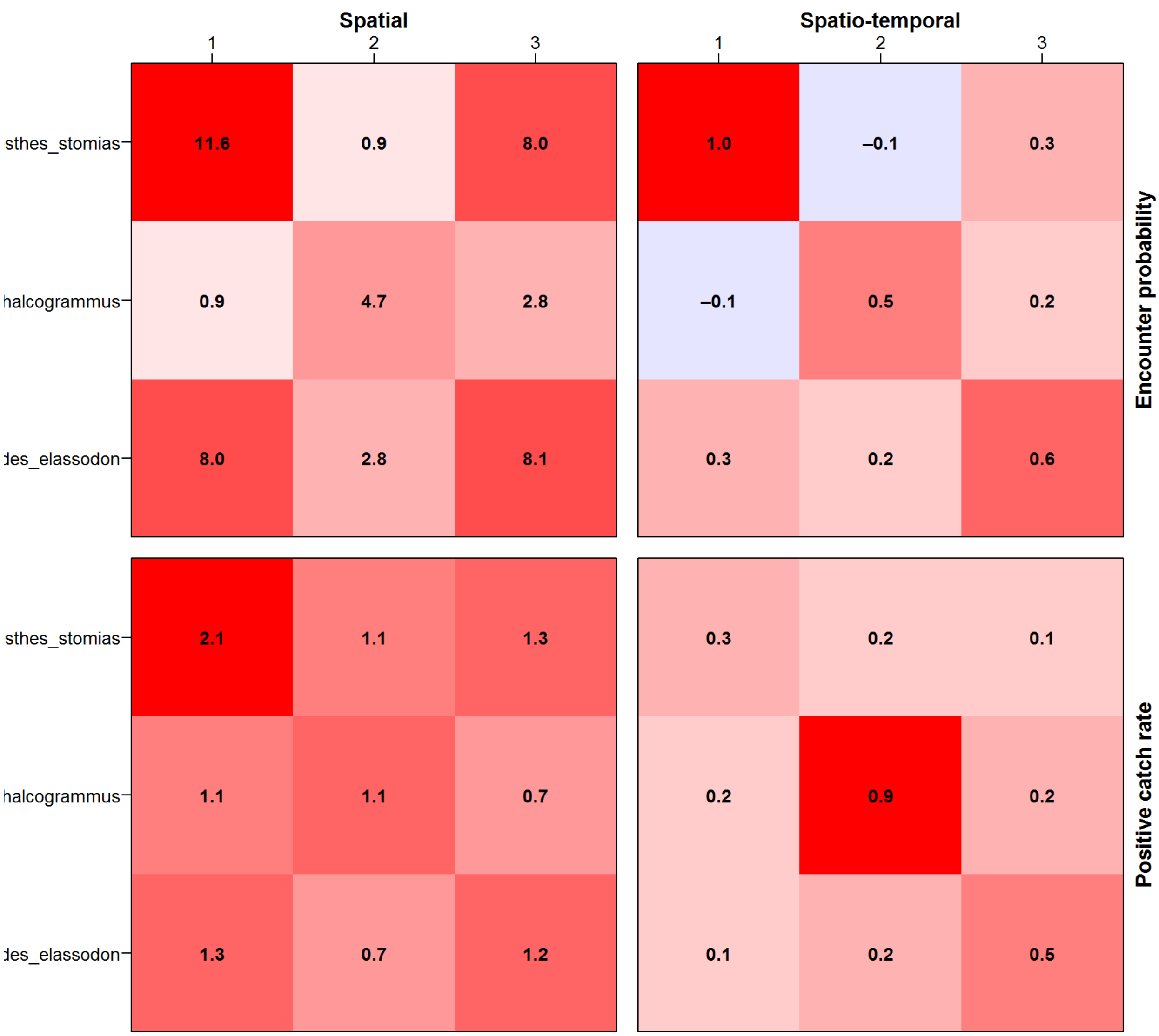

Figure 5: Spatial and spatio-temporal covariance

```r
# Get region-specific settings for plots
MapDetails_List = SpatialDeltaGLMM::MapDetails_Fn(Region = Region,
    NN_Extrap = Spatial_List$PolygonList$NN_Extrap,
    Extrapolation_List = Extrapolation_List)
# Plot maps representing density or other variables
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"]))
```

7.4 Index of abundance

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

```r
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	159190	15511
Atheresthes_stomias	1986	192115	18334
Atheresthes_stomias	1987	282950	25800
Atheresthes_stomias	1988	286337	26542
Atheresthes_stomias	1989	329650	28784
Atheresthes_stomias	1990	371867	34531
Atheresthes_stomias	1991	263359	26139
Atheresthes_stomias	1992	291365	30620
Atheresthes_stomias	1993	413322	36091
Atheresthes_stomias	1994	456732	44291
Atheresthes_stomias	1995	391251	40100
Atheresthes_stomias	1996	486618	44812
Atheresthes_stomias	1997	387239	36275
Atheresthes_stomias	1998	306539	27454
Atheresthes_stomias	1999	185833	19306
Atheresthes_stomias	2000	277584	25497
Atheresthes_stomias	2001	342031	30674
Atheresthes_stomias	2002	276770	24311
Atheresthes_stomias	2003	497707	40160

Category	Year	Estimate_metric_tons	SD_mt
Atheresthes_stomias	2004	514974	42567
Atheresthes_stomias	2005	693423	55143
Atheresthes_stomias	2006	559049	48919
Atheresthes_stomias	2007	446584	40009
Atheresthes_stomias	2008	477890	42434
Atheresthes_stomias	2009	362742	33808
Atheresthes_stomias	2010	520132	46941
Atheresthes_stomias	2011	498272	42279
Atheresthes_stomias	2012	365703	33920
Atheresthes_stomias	2013	380567	34986
Atheresthes_stomias	2014	469430	39297
Atheresthes_stomias	2015	414551	34492
Atheresthes_stomias	2016	521984	39352
Gadus_chalcogrammus	1982	2443412	211827
Gadus_chalcogrammus	1983	5862957	518711
Gadus_chalcogrammus	1984	4055642	354974
Gadus_chalcogrammus	1985	4608462	449562
Gadus_chalcogrammus	1986	4432971	401041
Gadus_chalcogrammus	1987	4903675	455186
Gadus_chalcogrammus	1988	6549125	643655
Gadus_chalcogrammus	1989	5908842	517502
Gadus_chalcogrammus	1990	6551141	729070
Gadus_chalcogrammus	1991	4693391	420686
Gadus_chalcogrammus	1992	4243910	393318
Gadus_chalcogrammus	1993	5053477	412701
Gadus_chalcogrammus	1994	4564137	387784
Gadus_chalcogrammus	1995	4372436	393454
Gadus_chalcogrammus	1996	2800742	220331
Gadus_chalcogrammus	1997	3351562	292777
Gadus_chalcogrammus	1998	2449507	204356
Gadus_chalcogrammus	1999	3419447	334999
Gadus_chalcogrammus	2000	4638386	400685
Gadus_chalcogrammus	2001	4018521	353177
Gadus_chalcogrammus	2002	4421406	347734
Gadus_chalcogrammus	2003	7416807	663532
Gadus_chalcogrammus	2004	3691162	301272
Gadus_chalcogrammus	2005	4418688	372832
Gadus_chalcogrammus	2006	2903149	260096
Gadus_chalcogrammus	2007	3956878	405949
Gadus_chalcogrammus	2008	2759972	286115
Gadus_chalcogrammus	2009	2003812	226413
Gadus_chalcogrammus	2010	3351565	336491
Gadus_chalcogrammus	2011	2933209	265811
Gadus_chalcogrammus	2012	3271415	273255
Gadus_chalcogrammus	2013	4259454	384217
Gadus_chalcogrammus	2014	7317187	570096
Gadus_chalcogrammus	2015	6333116	485372
Gadus_chalcogrammus	2016	4589910	339786
Hippoglossoides_elassodon	1982	190158	15384
Hippoglossoides_elassodon	1983	243392	18184
Hippoglossoides_elassodon	1984	253020	20490
Hippoglossoides_elassodon	1985	246101	19249

Category	Year	Estimate_metric_tons	SD_mt
Hippoglossoides_elassodon	1986	322159	25283
Hippoglossoides_elassodon	1987	370796	29876
Hippoglossoides_elassodon	1988	504260	39501
Hippoglossoides_elassodon	1989	470716	36459
Hippoglossoides_elassodon	1990	549519	43221
Hippoglossoides_elassodon	1991	515736	41335
Hippoglossoides_elassodon	1992	567639	44681
Hippoglossoides_elassodon	1993	578248	45517
Hippoglossoides_elassodon	1994	649208	51091
Hippoglossoides_elassodon	1995	553243	44921
Hippoglossoides_elassodon	1996	575392	45093
Hippoglossoides_elassodon	1997	711443	57595
Hippoglossoides_elassodon	1998	646763	53506
Hippoglossoides_elassodon	1999	354328	28829
Hippoglossoides_elassodon	2000	364289	27771
Hippoglossoides_elassodon	2001	466217	36078
Hippoglossoides_elassodon	2002	503610	38315
Hippoglossoides_elassodon	2003	469802	35325
Hippoglossoides_elassodon	2004	573280	42320
Hippoglossoides_elassodon	2005	612228	45585
Hippoglossoides_elassodon	2006	572856	42731
Hippoglossoides_elassodon	2007	548479	42900
Hippoglossoides_elassodon	2008	488285	37764
Hippoglossoides_elassodon	2009	359243	30357
Hippoglossoides_elassodon	2010	407601	32436
Hippoglossoides_elassodon	2011	510627	43116
Hippoglossoides_elassodon	2012	346193	28211
Hippoglossoides_elassodon	2013	414887	36025
Hippoglossoides_elassodon	2014	469585	36041
Hippoglossoides_elassodon	2015	369205	27642
Hippoglossoides_elassodon	2016	427499	30173

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)
```

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"),
```

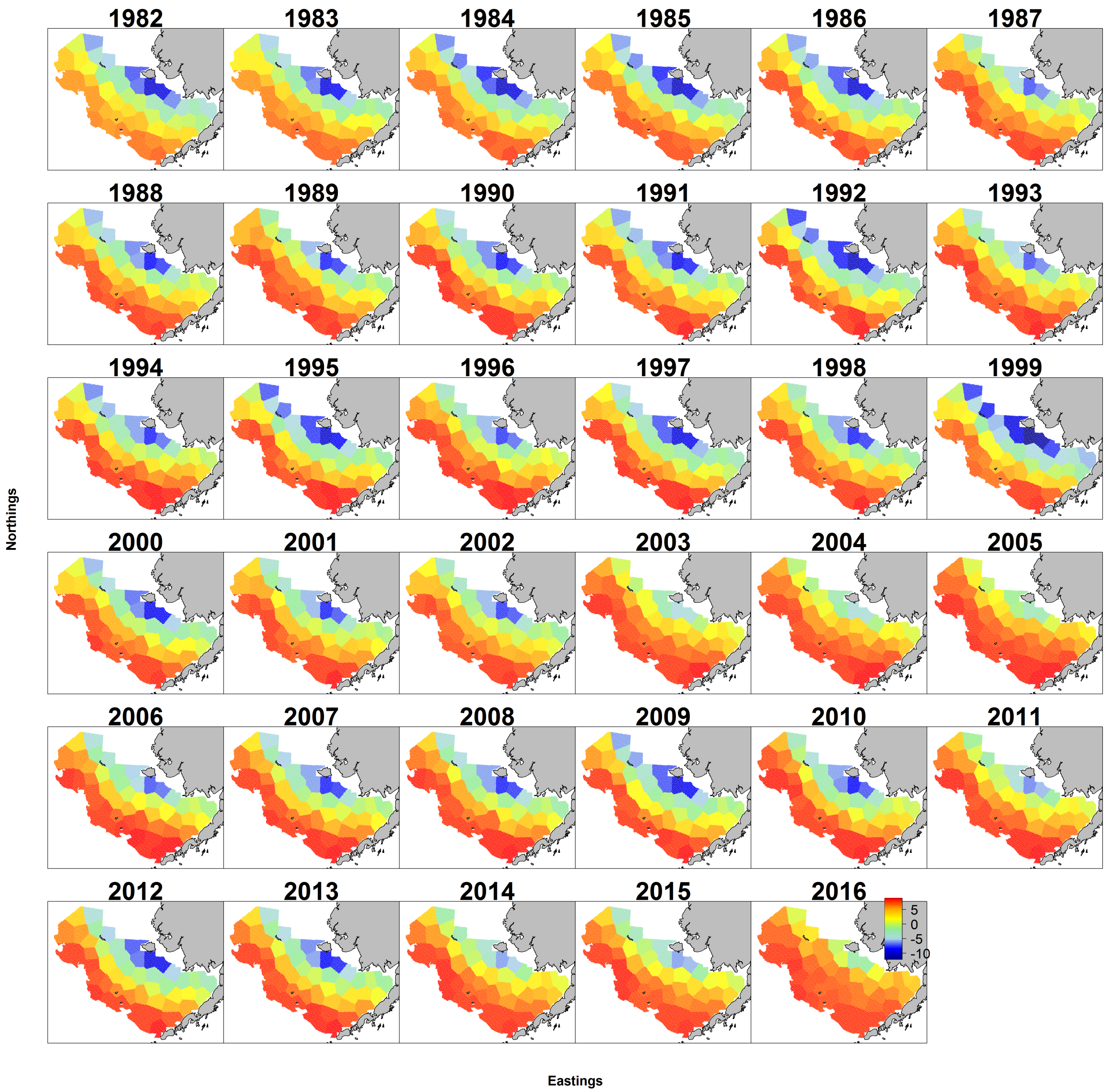

Figure 6: Density maps for each year for arrowtooth flounder

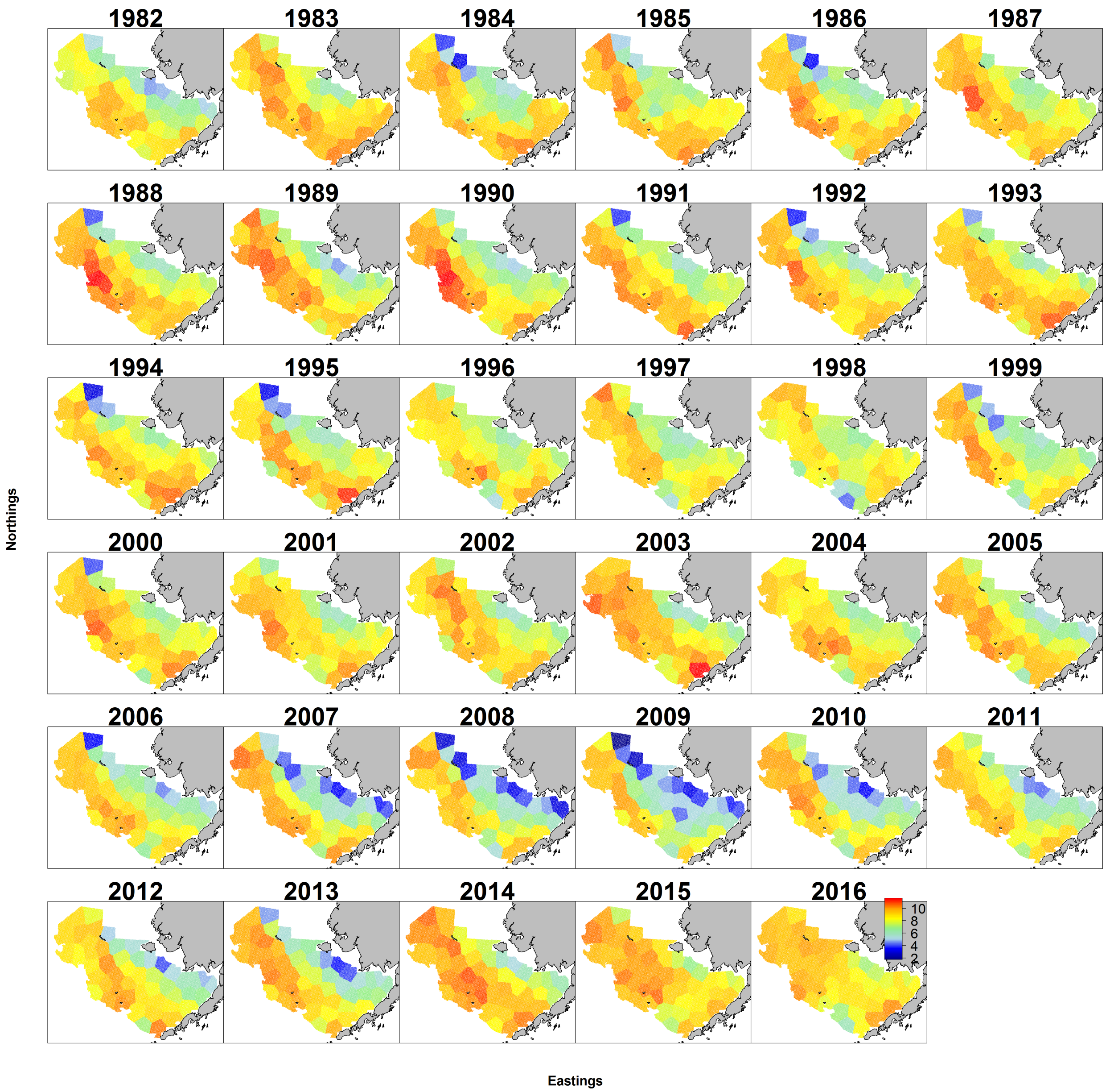

Figure 7: Density maps for each year for Alaska pollock

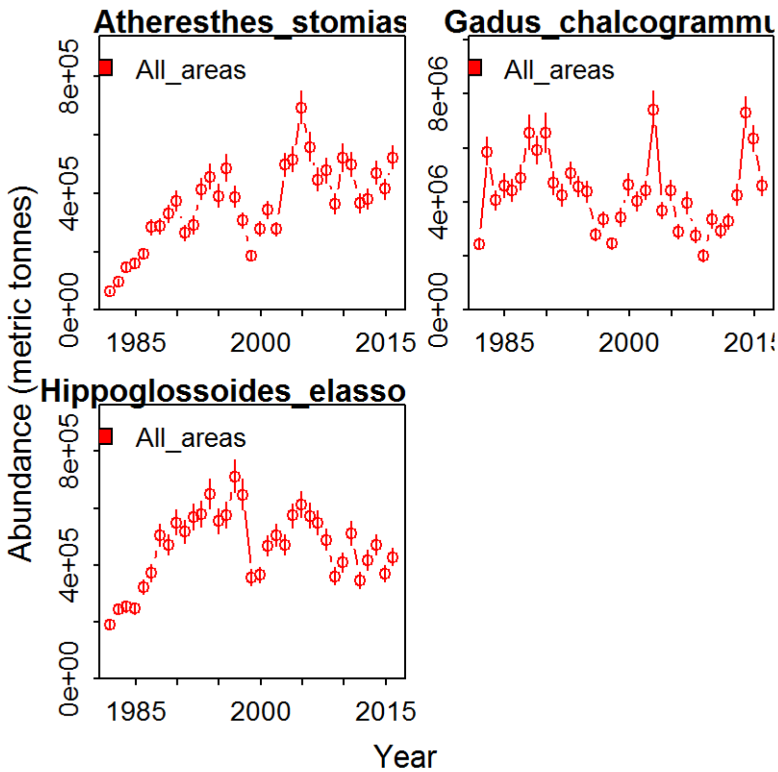

Figure 8: Index of abundance plus/minus 1 standard error

```
    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)
```

```
## Warning: package 'maps' was built under R version
## 3.2.5

## Warning: package 'maps' was built under R version
## 3.2.5
```

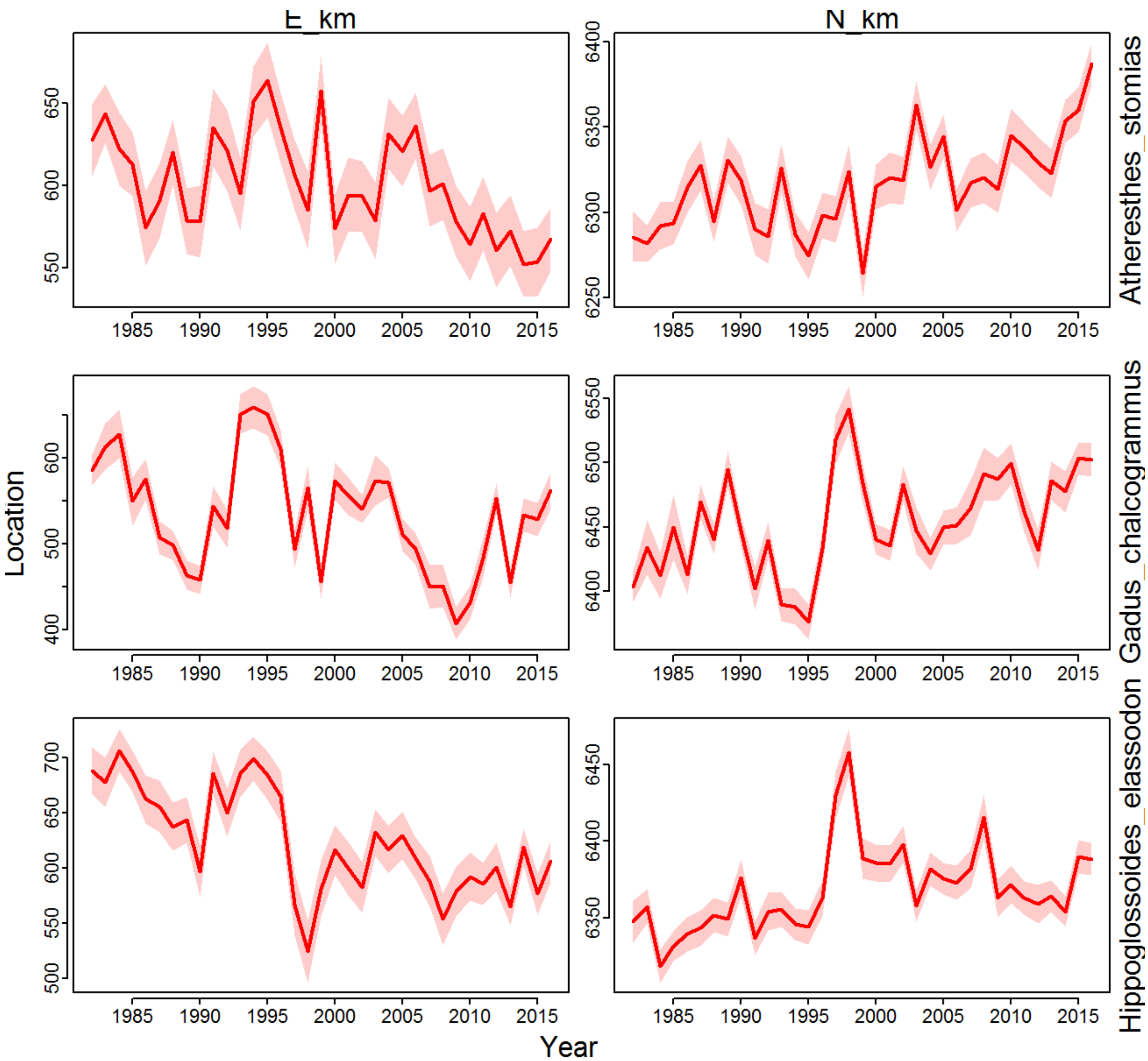

Figure 9: Center of gravity (COG) indicating shifts in distribution plus/minus 1 standard error

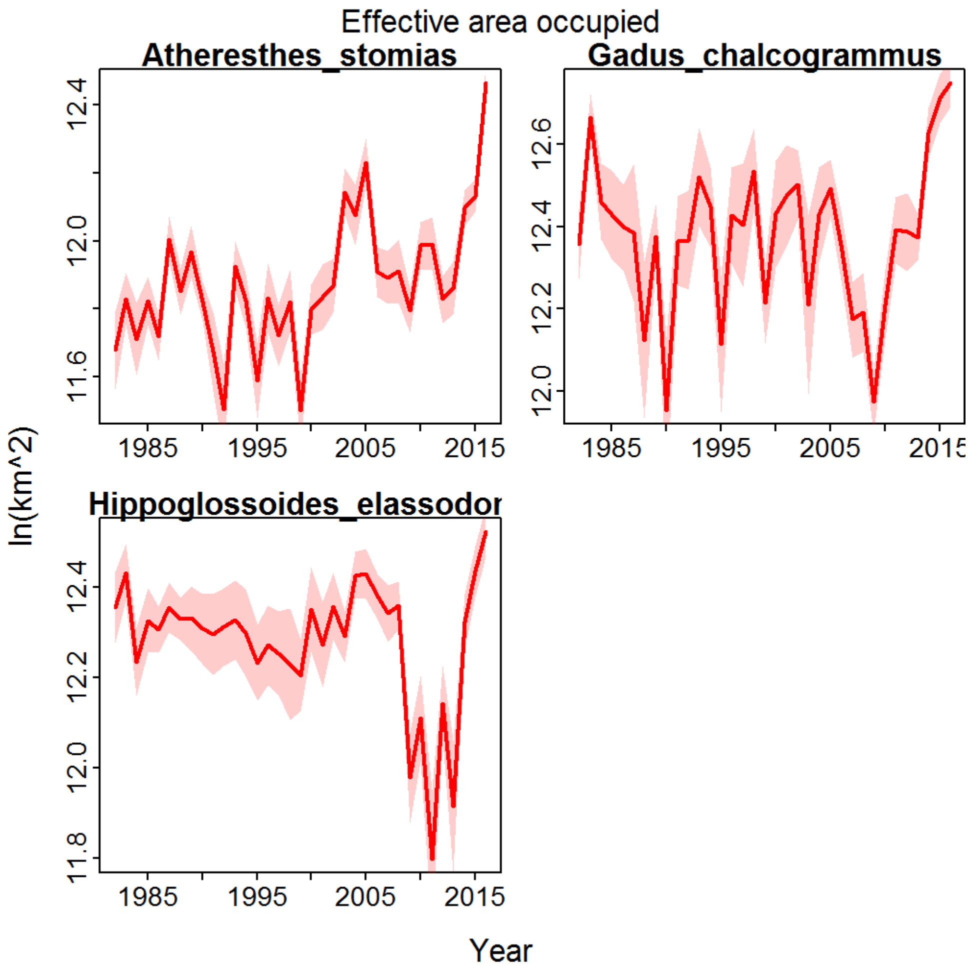

Figure 10: Effective area occupied indicating range expansion/contraction plus/minus 1 standard error

```
## Warning: package 'maps' was built under R version
## 3.2.5

## Warning: package 'maps' was built under R version
## 3.2.5

## Warning: package 'maps' was built under R version
## 3.2.5

## Warning: package 'maps' was built under R version
## 3.2.5

## Warning: package 'maps' was built under R version
## 3.2.5

## Warning: package 'maps' was built under R version
## 3.2.5

## Warning: package 'maps' was built under R version
## 3.2.5

## Warning: package 'maps' was built under R version
## 3.2.5
```

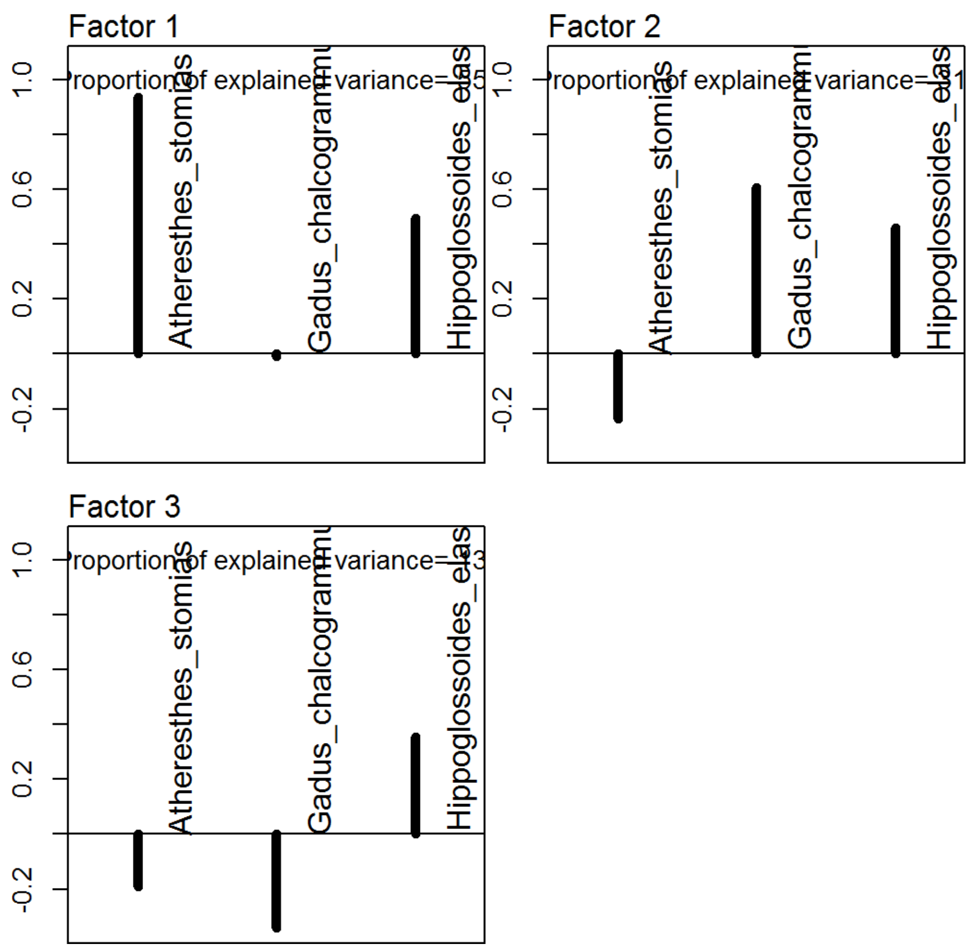

Figure 11: Factor loadings for spatio-temporal variation in encounter probability

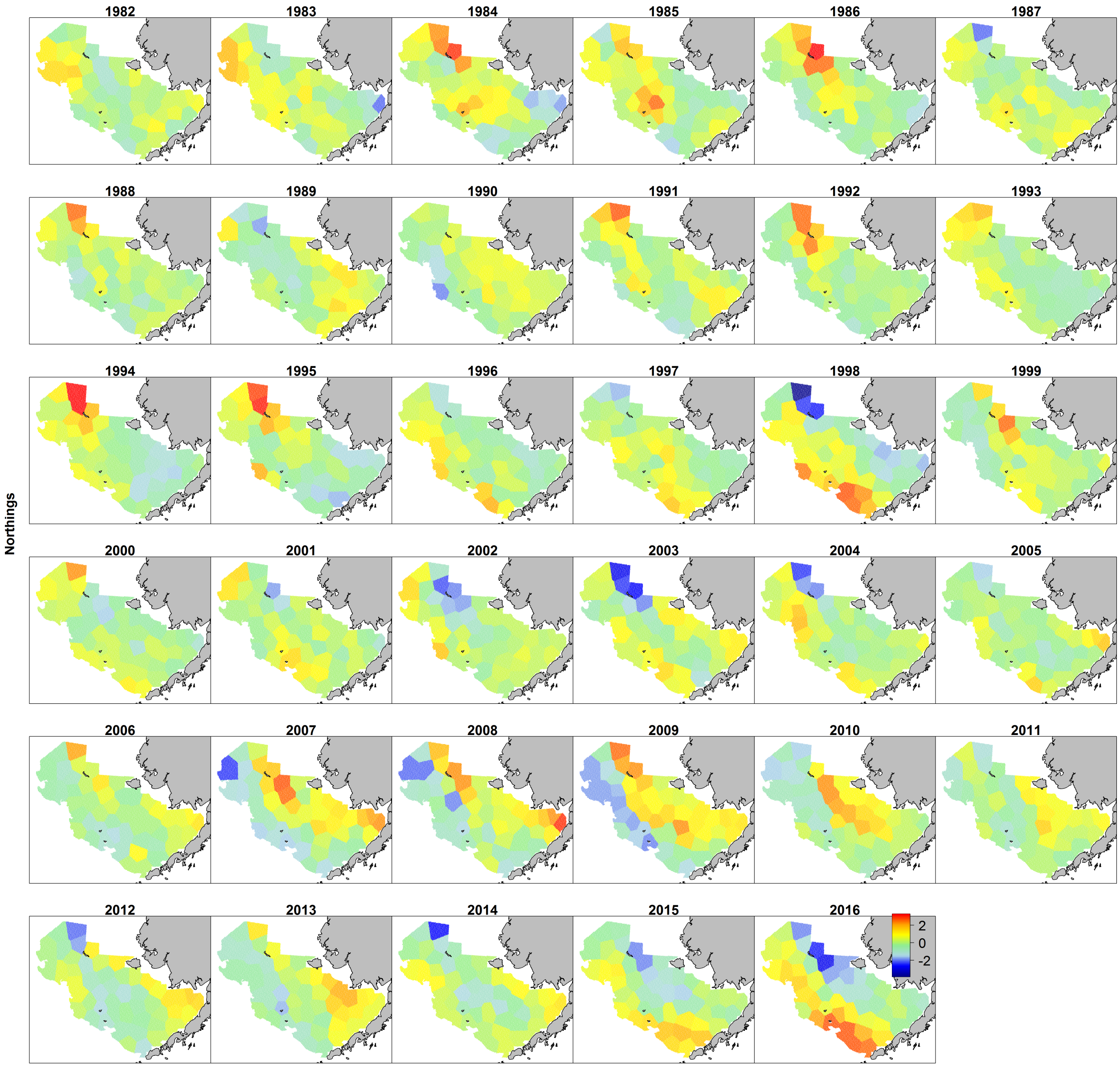

Figure 12: Factor maps for dominant (first) factor for spatio-temporal variation in positive catch rates