

Supporting information for ‘The Point Process Framework for Integrated Modelling of Biodiversity Data’

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Setup

These are the packages we will be using:

```
#devtools::install_github("PhilipMostert/PointedSDMs")
library(PointedSDMs) # model fitting
library(ggplot2)     # plotting
library(raster)      # plotting
library(mapproj)    # map options for plotting
library(INLA)        # functions for specifying mesh
library(dplyr)       # data handling
library(sf)          # spatial stuff
library(showtext)    # font for plot
library(patchwork)   # combining figures
```

Downloading data

Before you run this file, make sure you have the following files in the given locations:

- data/environmental_covariates.rds
 - should be in the data folder already.
- data/Norwegian_lakes.rds
 - can be downloaded from <https://bird.unit.no/resources/9b27e8f0-55dd-442c-be73-26781dad94c8/> content, click on “Innhold”-tab at the bottom of the page and select “Norwegian_lakes.rds”.
- data/artsobs_clean.rds
 - created from running the script R/data_preparation.R, see further instructions there.
- data/survey_clean.rds
 - also created from running the script R/data_preparation.R, see further instructions there.

Loading Norway map and making mesh

We begin by making a spatial mesh out of a map of Norway.

```

proj <- '+proj=utm +zone=32 +datum=WGS84 +units=km +no_defs' #m
norwayfill <- maps::map("world", "norway", fill=TRUE, plot=FALSE,
                        ylim=c(58,72), xlim=c(4,32))
IDs <- sapply(strsplit(norwayfill$names, ":"), function(x) x[1])
norway.poly <- spTransform(mapproj::map2SpatialPolygons(norwayfill, IDs = IDs,
                                                       proj4string = CRS('+proj=lonlat +zone=32 +datum=WGS84 +units=m +no_defs')), proj)

```

Adjusting the mesh to be coarser is the easiest way to decrease the run-time for the model. With the following mesh, the model estimation takes a long time to complete, but feel free to change the `max.edge` or `cutoff` to get a coarser mesh.

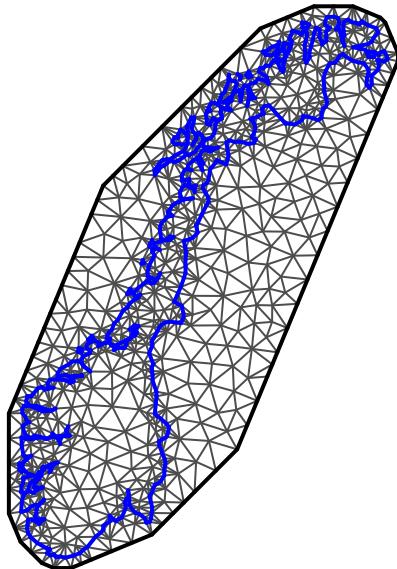
```

mesh <- inla.mesh.2d(boundary = inla.sp2segment(norway.poly),
                      cutoff = 0.3 * 30, # smallest allowed distance between points
                      max.edge = c(6, 3) * 30, # decrease this for more int. points
                      #max.edge = c(3, 1),
                      offset = c(1, 1) * 30,
                      crs = st_crs(proj))

ipoints = st_as_sf(fm_int(mesh, norway.poly,
                           int.args = list(method = 'direct')))

plot(mesh)

```



Setting up covariate data

Next we load the environmental data, which will be used as covariates in our model.

```

covariates_raw <- readRDS("data/environmental_covariates.RDS")

covariates <- covariates_raw %>%
  # Log-transform area of lake
  dplyr::mutate(log_area = log(area_km2)) %>%
  # Log-transform catchment area of lake
  dplyr::mutate(log_catchment = log(catchment_area_km2)) %>%
  # Remove some uninformative variables

```

```

dplyr::select(-c(ebint, no_vatn_lnr, eb_waterregionID))

# Choose from
# "decimalLatitude", "decimalLongitude",
# "log_area", "perimeter_m", "distance_to_road",
# "eurolst_bio10", "catchment_area_km2", "SCI", "HFP"

Use <- c("SCI", 'HFP')

cov_pixel <- SpatialPixelsDataFrame(
  points = covariates[,c("decimalLongitude", "decimalLatitude")],
  data = data.frame(covariates[,Use]),
  proj4string = CRS('+proj=lonlat +zone=32 +datum=WGS84 +units=m +no_defs'),
  tol = 0.340571)
if (length(Use) == 1) names(cov_pixel@data) <- Use
# Scale covariates and convert to terra::rast
cov_raster <- terra::project(scale(terra::rast(cov_pixel)), proj)

```

Observation data

For this model, we have two observation sets, one which is downloaded from GBIF and one that is a survey dataset (see separate document for download instructions).

```

fishes <- c("Esox_lucius", "Perca_fluviatilis", "Salmo_trutta", "Salvelinus_alpinus")

survey <- readRDS("data/survey_clean.rds") %>%
  filter(species %in% fishes) %>%
  st_as_sf(coords = c("decimalLongitude", "decimalLatitude"),
            crs = '+proj=lonlat +zone=32 +datum=WGS84 +units=m +no_defs') %>%
  mutate(decimalLongitude = st_coordinates(.)[,1], decimalLatitude = st_coordinates(.)[,2]) %>%
  st_transform(proj)

artsobs <- readRDS("data/artsobs_clean.rds") %>%
  filter(species %in% fishes) %>%
  st_as_sf(coords = c("decimalLongitude", "decimalLatitude"),
            crs = '+proj=lonlat +zone=32 +datum=WGS84 +units=m +no_defs') %>%
  mutate(decimalLongitude = st_coordinates(.)[,1], decimalLatitude = st_coordinates(.)[,2]) %>%
  st_transform(proj)

```

We can plot the observed data points:

```

showtext_auto()
showtext_opts(dpi = 300)
f1 <- "Open sans"
font_add_google(f1, f1)

norway <- ggplot2::map_data("world", region = "Norway(?!:Svalbard)")
norway <- setdiff(norway, dplyr::filter(norway, subregion == "Jan Mayen"))

p_artsobs <- ggplot(artsobs, aes(x = decimalLongitude, y = decimalLatitude)) +
  geom_polygon(data = norway, aes(long, lat, group = group),
               color = "grey80", fill = "grey95") +
  geom_point(color = "darkorange2", size = 0.5, alpha = 0.3) +
  facet_wrap(~species, nrow = 1,
             labeller = labeller(species = function(string) sub("_", " ", string))) +

```

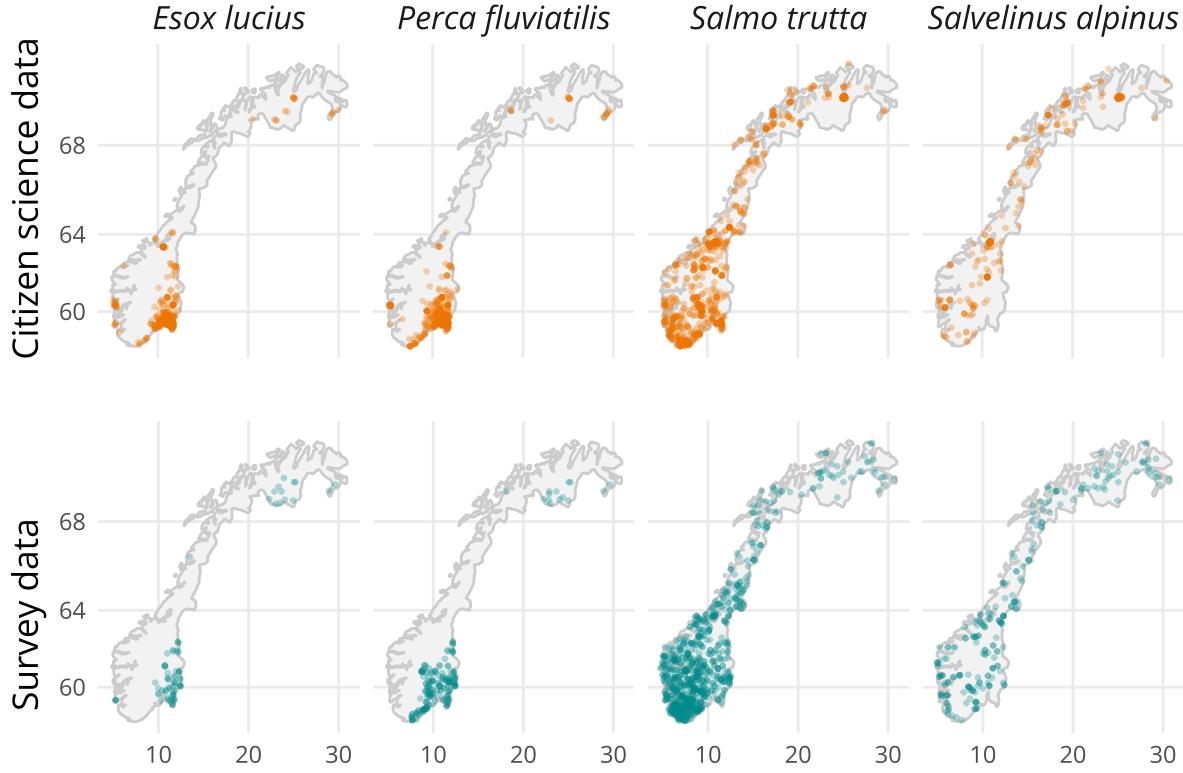
```

coord_map() +
labs(tag = "Citizen science data") +
theme_minimal() +
theme(text = element_text(family = f1),
      strip.text = element_text(family = f1, size = 12, face = "italic"),
      plot.tag = element_text(angle = 90, hjust = 0.5),
      plot.tag.position = c(-0.03, 0.45),
      legend.position = "none",
      axis.title = element_blank(),
      axis.text.x = element_blank())

p_survey <- ggplot(survey %>% filter(occurrenceStatus == 1),
                    aes(x = decimalLongitude, y = decimalLatitude)) +
  geom_polygon(data = norway, aes(long, lat, group = group),
               color="grey80", fill = "grey95") +
  geom_jitter(color = "darkcyan", size = 0.5, alpha = 0.3) +
  facet_wrap(~species, nrow = 1) +
  coord_map() +
  xlab("Longitude") +
  ylab("Latitude") +
  labs(tag = "Survey data") +
  theme_minimal() +
  theme(text = element_text(family = f1),
        plot.tag = element_text(angle = 90, hjust = 0.5),
        plot.tag.position = c(-0.03, 0.45),
        legend.position = "none",
        axis.title = element_blank(),
        strip.text = element_blank(),
        plot.margin = margin(l = 30))

p_artsobs / p_survey

```



```
ggsave("figures/presence_points.pdf", height = 5, width = 8)
ggsave("figures/presence_points.png", height = 5, width = 8)
```

Separate models for the two datasets

For the presence/absence survey data, we use a Bernoulli distribution, where the presence probability for species $j \in \{Salmo trutta, Perca fluviatilis, Esox lucius, Salvelinus alpinus\}$ depends on some covariates $x(s)$, along with a spatial field $\xi_j(s)$:

$$Y_{PA,j}(s_i) \sim \text{Bernoulli}(p_{PA,j}(s_i))$$

$$\text{cloglog}(p_{PA,j}(s_i)) = \alpha_{PA,j} + x(s_i)^T \beta_j + \xi_j(s_i).$$

We first prepare the model using the `intModel` function.

```
surveyModel <- intModel(
  survey,                                # Survey data
  Boundary = st_as_sf(norway.poly),        # Boundary
  IPS = ipoints,                          # integration points
  spatialCovariates = cov_raster,         # Covariates
  speciesName = "species",                # The column containing species name
  Coordinates = c("decimalLongitude", "decimalLatitude"), # Name of coords
  responsePA = "occurrenceStatus",        # Name of response column
  pointsSpatial = NULL,                  # NULL since we use speciesSpatial
  Mesh = mesh,                            # inla mesh object
  Projection = proj                      # CRS for points and covariates
)
```

We then specify priors for the spatial effects using `$.specifySpatial`.

```

for (fish in fishes) {

  surveyModel$specifySpatial(Species = fish,
                             prior.range = c(50, 0.01),
                             prior.sigma = c(1, 0.01))
}

```

And fit the model using `fitISDM`.

```

surveyFit <- fitISDM(surveyModel,
                      options = list(num.threads = 2,
                                    control.inla = list(int.strategy = 'eb',
                                                       cmin = 0,
                                                       strategy = 'adaptive'),
                                    safe = TRUE,
                                    inla.mode = 'experimental'))

summary(surveyFit)

## Summary of 'bruSDM' object:
##
## inlabru version: 2.10.1
## INLA version: 24.02.20
##
## Types of data modelled:
##
## survey           Present absence
##
## Summary of the fixed effects for the species:
##
## Summary for Perca_fluviatilis:
##               mean        sd 0.025quant  0.5quant
## Perca_fluviatilis_SCI -0.2238641 0.1370506 -0.4924782 -0.2238641
## Perca_fluviatilis_HFP -0.1313879 0.1150367 -0.3568558 -0.1313879
## Perca_fluviatilis_intercept -3.9293015 1.4121526 -6.6970697 -3.9293015
##                           0.975quant   mode kld
## Perca_fluviatilis_SCI 0.04475012 -0.2238641 0
## Perca_fluviatilis_HFP 0.09407992 -0.1313879 0
## Perca_fluviatilis_intercept -1.16153320 -3.9293015 0
##
## Summary for Salmo_trutta:
##               mean        sd 0.025quant  0.5quant
## Salmo_trutta_SCI -0.002098916 0.06796368 -0.1353053 -0.002098916
## Salmo_trutta_HFP 0.011769073 0.05816205 -0.1022264 0.011769073
## Salmo_trutta_intercept 0.908492244 0.38282423 0.1581705 0.908492244
##                           0.975quant   mode kld
## Salmo_trutta_SCI 0.1311074 -0.002098916 0
## Salmo_trutta_HFP 0.1257646 0.011769073 0
## Salmo_trutta_intercept 1.6588139 0.908492244 0
##
## Summary for Salvelinus_alpinus:
##               mean        sd 0.025quant  0.5quant
## Salvelinus_alpinus_SCI -0.04750528 0.08916350 -0.22226254 -0.04750528
## Salvelinus_alpinus_HFP 0.09632022 0.07747017 -0.05551852 0.09632022

```

```

## Salvelinus_alpinus_intercept -1.17238348 0.23905175 -1.64091630 -1.17238348
##                                     0.975quant      mode kld
## Salvelinus_alpinus_SCI        0.1272520 -0.04750528   0
## Salvelinus_alpinus_HFP        0.2481590  0.09632022   0
## Salvelinus_alpinus_intercept -0.7038507 -1.17238348   0
##
## Summary for Esox_lucius:
##                               mean      sd 0.025quant 0.5quant 0.975quant
## Esox_lucius_SCI      -0.1658093 0.1766482 -0.5120335 -0.1658093 0.1804149
## Esox_lucius_HFP       0.5831531 0.1237827  0.3405436  0.5831531 0.8257627
## Esox_lucius_intercept -3.6985240 1.0468948 -5.7504001 -3.6985240 -1.6466479
##                                     mode kld
## Esox_lucius_SCI      -0.1658093   0
## Esox_lucius_HFP       0.5831531   0
## Esox_lucius_intercept -3.6985240   0

## Time used:
##     Pre = 1.72, Running = 22.9, Post = 0.298, Total = 24.9
## Random effects:
##   Name      Model
##   Perca_fluviatilis_survey_spatial SPDE2 model
##   Salmo_trutta_survey_spatial SPDE2 model
##   Salvelinus_alpinus_survey_spatial SPDE2 model
##   Esox_lucius_survey_spatial SPDE2 model
##
## Model hyperparameters:
##                               mean      sd 0.025quant 0.5quant
## Range for Perca_fluviatilis_survey_spatial 350.108 62.776 246.633 343.376
## Stdev for Perca_fluviatilis_survey_spatial  2.916  0.421  2.180  2.884
## Range for Salmo_trutta_survey_spatial      393.307 128.189 201.988 373.337
## Stdev for Salmo_trutta_survey_spatial       0.774  0.196  0.464  0.748
## Range for Salvelinus_alpinus_survey_spatial 75.832 12.873 53.549 74.797
## Stdev for Salvelinus_alpinus_survey_spatial  1.653  0.191  1.302  1.645
## Range for Esox_lucius_survey_spatial        373.688 115.974 200.022 355.783
## Stdev for Esox_lucius_survey_spatial         2.131  0.407  1.450  2.091
##                                     0.975quant      mode
## Range for Perca_fluviatilis_survey_spatial 492.90 328.234
## Stdev for Perca_fluviatilis_survey_spatial  3.83  2.819
## Range for Salmo_trutta_survey_spatial       700.94 336.195
## Stdev for Salmo_trutta_survey_spatial        1.23  0.698
## Range for Salvelinus_alpinus_survey_spatial 104.08 72.824
## Stdev for Salvelinus_alpinus_survey_spatial  2.05  1.634
## Range for Esox_lucius_survey_spatial        651.93 321.850
## Stdev for Esox_lucius_survey_spatial         3.04  2.009
##
## Deviance Information Criterion (DIC) .....: 1614.48
## Deviance Information Criterion (DIC, saturated) ....: 1614.43
## Effective number of parameters .....: 208.41
##
## Watanabe-Akaike information criterion (WAIC) ....: 1648.04
## Effective number of parameters .....: 189.71
##
## Marginal log-Likelihood: -970.07
## is computed

```

```
## Posterior summaries for the linear predictor and the fitted values are computed
## (Posterior marginals needs also 'control.compute=list(return.marginals.predictor=TRUE)')
```

The presence-only data is fitted with a Poisson point process model, where the intensity depends on the same covariates $x(s)$ and the same spatial field $\xi_j(s)$. In the ISDM, we will add an additional spatial field $\xi_{\text{bias}}(s)$ that is unique to the citizen science data, but shared across all fish species:

$$Y_{PO,j}(s_i) \sim \text{Poisson}(e^{\eta_{PO,j}(s_i)})$$

$$\eta_{PO,j}(s_i) = \alpha_{PO,j} + x(s)^T \beta_j + \xi_j(s_i) + \xi_{\text{bias}}(s_i).$$

```
artsobsModel <- intModel(
  artsobs,
  Boundary = st_as_sf(norway.poly), # Boundary
  IPS = ipoints, # integration points
  spatialCovariates = cov_raster, # Covariates
  speciesName = "species", # The column containing species name
  Coordinates = c("decimalLongitude", "decimalLatitude"), # Name of coords
  responsePA = "occurrenceStatus", # Name of response column
  pointsSpatial = NULL, # NULL since we use speciesSpatial
  Mesh = mesh, # inla mesh object
  Projection = proj # CRS for points and covariates
)

for (fish in fishes) {

  artsobsModel$specifySpatial(Species = fish,
                               prior.range = c(50, 0.01),
                               prior.sigma = c(1, 0.01))
}

artsobsFit <- fitISDM(artsobsModel,
                      options = list(num.threads = 2,
                                    control.inla = list(int.strategy = 'eb',
                                                       cmin = 0,
                                                       strategy = 'gaussian'),
                                    safe = TRUE,
                                    inla.mode = 'experimental'))

summary(artsobsFit)

## Summary of 'bruSDM' object:
##
## inlabru version: 2.10.1
## INLA version: 24.02.20
##
## Types of data modelled:
##
## artsobs Present only
##
## Summary of the fixed effects for the species:
##
## Summary for Salvelinus_alpinus:
##                                     mean          sd 0.025quant   0.5quant
## Salvelinus_alpinus_SCI      0.01095453 0.06519605 -0.1168274  0.01095453
## Salvelinus_alpinus_HFP     -0.12668474 0.06253779 -0.2492566 -0.12668474
```

```

## Salvelinus_alpinus_intercept -8.30576370 0.24361009 -8.7832307 -8.30576370
##                                     0.975quant      mode kld
## Salvelinus_alpinus_SCI          0.138736443 0.01095453 0
## Salvelinus_alpinus_HFP         -0.004112915 -0.12668474 0
## Salvelinus_alpinus_intercept -7.828296693 -8.30576370 0
##
## Summary for Esox_lucius:
##                               mean        sd 0.025quant 0.5quant 0.975quant
## Esox_lucius_SCI      -0.1571871 0.05627231 -0.26747880 -0.1571871 -0.04689539
## Esox_lucius_HFP      0.1072735 0.03303235  0.04253131 0.1072735 0.17201576
## Esox_lucius_intercept -9.3058090 0.48337829 -10.25321306 -9.3058090 -8.35840499
##                                     mode kld
## Esox_lucius_SCI      -0.1571871 0
## Esox_lucius_HFP      0.1072735 0
## Esox_lucius_intercept -9.3058090 0
##
## Summary for Salmo_trutta:
##                               mean        sd 0.025quant 0.5quant
## Salmo_trutta_SCI     -0.05865531 0.03737706 -0.13191300 -0.05865531
## Salmo_trutta_HFP     0.04126777 0.03018890 -0.01790139 0.04126777
## Salmo_trutta_intercept -6.94224332 0.19711841 -7.32858831 -6.94224332
##                                     0.975quant      mode kld
## Salmo_trutta_SCI     0.01460238 -0.05865531 0
## Salmo_trutta_HFP     0.10043693 0.04126777 0
## Salmo_trutta_intercept -6.55589833 -6.94224332 0
##
## Summary for Perca_fluviatilis:
##                               mean        sd 0.025quant 0.5quant
## Perca_fluviatilis_SCI    -0.16730923 0.04228149 -0.25017942 -0.16730923
## Perca_fluviatilis_HFP     0.06696083 0.02566446  0.01665941 0.06696083
## Perca_fluviatilis_intercept -9.34631950 0.56315432 -10.45008169 -9.34631950
##                                     0.975quant      mode kld
## Perca_fluviatilis_SCI    -0.08443904 -0.16730923 0
## Perca_fluviatilis_HFP     0.11726225 0.06696083 0
## Perca_fluviatilis_intercept -8.24255730 -9.34631950 0
##
## Time used:
##     Pre = 3.18, Running = 77.4, Post = 3.1, Total = 83.7
##
## Random effects:
##   Name      Model
##   Salvelinus_alpinus_artobs_spatial SPDE2 model
##   Esox_lucius_artobs_spatial SPDE2 model
##   Salmo_trutta_artobs_spatial SPDE2 model
##   Perca_fluviatilis_artobs_spatial SPDE2 model
##
## Model hyperparameters:
##                               mean        sd 0.025quant 0.5quant
## Range for Salvelinus_alpinus_artobs_spatial 32.91 3.602      26.66   32.62
## Stdev for Salvelinus_alpinus_artobs_spatial  3.44 0.215       3.03    3.44
## Range for Esox_lucius_artobs_spatial        80.96 8.196      66.74   80.32
## Stdev for Esox_lucius_artobs_spatial        3.11 0.208       2.73    3.10
## Range for Salmo_trutta_artobs_spatial       35.20 3.200      29.48   35.00
## Stdev for Salmo_trutta_artobs_spatial       2.87 0.135       2.62    2.87
## Range for Perca_fluviatilis_artobs_spatial 91.05 8.112      76.34   90.62

```

```

## Stdev for Perca_fluviatilis_artsobs_spatial 3.29 0.237      2.86      3.28
##                                         0.975quant mode
## Range for Salvelinus_alpinus_artsobs_spatial 40.81 31.88
## Stdev for Salvelinus_alpinus_artsobs_spatial 3.88 3.44
## Range for Esox_lucius_artsobs_spatial       98.95 78.55
## Stdev for Esox_lucius_artsobs_spatial       3.55 3.08
## Range for Salmo_trutta_artsobs_spatial     42.07 34.49
## Stdev for Salmo_trutta_artsobs_spatial     3.15 2.86
## Range for Perca_fluviatilis_artsobs_spatial 108.25 89.63
## Stdev for Perca_fluviatilis_artsobs_spatial 3.79 3.25
##
## Deviance Information Criterion (DIC) ....: -35323.94
## Deviance Information Criterion (DIC, saturated) ....: NA
## Effective number of parameters ....: -41728.84
##
## Watanabe-Akaike information criterion (WAIC) ....: 21055.17
## Effective number of parameters ....: 7244.88
##
## Marginal log-Likelihood: -25341.10
## is computed
## Posterior summaries for the linear predictor and the fitted values are computed
## (Posterior marginals needs also 'control.compute=list(return.marginals.predictor=TRUE)')

```

Joint model for four fish species

Now we will fit two IDMS, one with the two datasets combined, and another with an additional spatial field for the citizen science data. Both these models will have four shared fields, shared across the data sets (survey/citizen science), but separate for each fish species. Since we have two data sets and four species, that means that we in total have eight sub-models.

```

ISDMsetup <- intModel(
  survey,                               # Survey data
  artsobs,                             # Citizen science data
  Boundary = st_as_sf(norway.poly),    # Boundary
  IPS = ipoints,                        # integration points
  spatialCovariates = cov_raster,     # Covariates
  speciesName = "species",             # The column containing species name
  speciesSpatial = "copy",              # Copy species fields across data
  Coordinates = c("decimalLongitude", "decimalLatitude"), # Name of coords
  responsePA = "occurrenceStatus",    # Name of response column
  pointsSpatial = NULL,                # NULL since we use speciesSpatial
  Mesh = mesh,                          # inla mesh object
  Projection = proj                   # CRS for points and covariates
)

for (fish in fishes) {

  ISDMsetup$specifySpatial(Species = fish,
                           prior.range = c(50, 0.01),
                           prior.sigma = c(1, 0.01))
}

```

For the species specific fields, the default in PointedSDMs is that these are allowed to be different up to a scaling factor (named beta in INLA) across the data sets. That means that for instance the trout-specific spatial field for the citizen science data set is equal to beta times the trout-specific spatial field for the survey

data. In practice, this has to do with the copy-option in INLA. But in our model we want them to be the same, not to vary by a factor. So we manually change this using the `$changeComponents` function, by setting `hyper = list(beta = list(fixed = TRUE))` for each of the four citizen science fields.

```
ISDMsetup$changeComponents(
  'Perca_fluviatilis_artobs_spatial(
    main = geometry,
    copy = "Perca_fluviatilis_survey_spatial",
    hyper = list(beta = list(fixed = TRUE)))',
    print = FALSE)

ISDMsetup$changeComponents(
  'Salmo_trutta_artobs_spatial(
    main = geometry,
    copy = "Salmo_trutta_survey_spatial",
    hyper = list(beta = list(fixed = TRUE)))',
    print = FALSE)

ISDMsetup$changeComponents(
  'Salvelinus_alpinus_artobs_spatial(
    main = geometry,
    copy = "Salvelinus_alpinus_survey_spatial",
    hyper = list(beta = list(fixed = TRUE)))',
    print = FALSE)

ISDMsetup$changeComponents(
  'Esox_lucius_artobs_spatial(
    main = geometry,
    copy = "Esox_lucius_survey_spatial",
    hyper = list(beta = list(fixed = TRUE)))')

## Components:
## --1 + Perca_fluviatilis_survey_spatial(main = geometry, model = Perca_fluviatilis_survey_field) +
##     Salmo_trutta_survey_spatial(main = geometry, model = Salmo_trutta_survey_field) +
##     Salvelinus_alpinus_survey_spatial(main = geometry, model = Salvelinus_alpinus_survey_field) +
##     Esox_lucius_survey_spatial(main = geometry, model = Esox_lucius_survey_field) +
##     Perca_fluviatilis_SCI(main = Perca_fluviatilis_SCI, model = "linear") +
##     Salmo_trutta_SCI(main = Salmo_trutta_SCI, model = "linear") +
##     Salvelinus_alpinus_SCI(main = Salvelinus_alpinus_SCI, model = "linear") +
##     Esox_lucius_SCI(main = Esox_lucius_SCI, model = "linear") +
##     Perca_fluviatilis_HFP(main = Perca_fluviatilis_HFP, model = "linear") +
##     Salmo_trutta_HFP(main = Salmo_trutta_HFP, model = "linear") +
##     Salvelinus_alpinus_HFP(main = Salvelinus_alpinus_HFP, model = "linear") +
##     Esox_lucius_HFP(main = Esox_lucius_HFP, model = "linear") +
##     Perca_fluviatilis_intercept(1) + Salmo_trutta_intercept(1) +
##     Salvelinus_alpinus_intercept(1) + Esox_lucius_intercept(1) +
##     Perca_fluviatilis_artobs_spatial(main = geometry, copy = "Perca_fluviatilis_survey_spatial",
##         hyper = list(beta = list(fixed = TRUE))) + Salmo_trutta_artobs_spatial(main = geometry,
##         copy = "Salmo_trutta_survey_spatial", hyper = list(beta = list(fixed = TRUE))) +
##         Salvelinus_alpinus_artobs_spatial(main = geometry, copy = "Salvelinus_alpinus_survey_spatial",
##             hyper = list(beta = list(fixed = TRUE))) + Esox_lucius_artobs_spatial(main = geometry,
##             copy = "Esox_lucius_survey_spatial", hyper = list(beta = list(fixed = TRUE)))
## <environment: 0x556b3f3df180>
```

We may look at which terms are included in each of the eight sub-models by calling `$updateFormula` with

the data sets as the arguments.

```
ISDMsetup$updateFormula(datasetName = "survey")

## $Perca_fluviatilis
## occurrenceStatus ~ Perca_fluviatilis_SCI + Perca_fluviatilis_HFP +
##     Perca_fluviatilis_survey_spatial + Perca_fluviatilis_intercept
## <environment: 0x556b552c21f8>
##
## $Salmo_trutta
## occurrenceStatus ~ Salmo_trutta_SCI + Salmo_trutta_HFP + Salmo_trutta_survey_spatial +
##     Salmo_trutta_intercept
## <environment: 0x556b552c21f8>
##
## $Salvelinus_alpinus
## occurrenceStatus ~ Salvelinus_alpinus_SCI + Salvelinus_alpinus_HFP +
##     Salvelinus_alpinus_survey_spatial + Salvelinus_alpinus_intercept
## <environment: 0x556b552c21f8>
##
## $Esox_lucius
## occurrenceStatus ~ Esox_lucius_SCI + Esox_lucius_HFP + Esox_lucius_survey_spatial +
##     Esox_lucius_intercept
## <environment: 0x556b552c21f8>

ISDMsetup$updateFormula(datasetName = "artsobs")

## $Salvelinus_alpinus
## geometry ~ Salvelinus_alpinus_SCI + Salvelinus_alpinus_HFP +
##     Salvelinus_alpinus_artsobs_spatial + Salvelinus_alpinus_intercept
## <environment: 0x556b552c21f8>
##
## $Esox_lucius
## geometry ~ Esox_lucius_SCI + Esox_lucius_HFP + Esox_lucius_artsobs_spatial +
##     Esox_lucius_intercept
## <environment: 0x556b552c21f8>
##
## $Salmo_trutta
## geometry ~ Salmo_trutta_SCI + Salmo_trutta_HFP + Salmo_trutta_artsobs_spatial +
##     Salmo_trutta_intercept
## <environment: 0x556b552c21f8>
##
## $Perca_fluviatilis
## geometry ~ Perca_fluviatilis_SCI + Perca_fluviatilis_HFP + Perca_fluviatilis_artsobs_spatial +
##     Perca_fluviatilis_intercept
## <environment: 0x556b552c21f8>

ISDM <- fitISDM(ISDMsetup,
                  options = list(num.threads = 2,
                                control.inla = list(int.strategy = 'eb',
                                                    cmin = 0,
                                                    strategy = 'gaussian'),
                                safe = TRUE,
                                inla.mode = 'experimental'))
```

We may then examine the model summary and save the model for future use.

```
summary(ISDM)
```

```
## Summary of 'bruSDM' object:  
##  
## inlabru version: 2.10.1  
## INLA version: 24.02.20  
##  
## Types of data modelled:  
##  
## survey Present absence  
## artsobs Present only  
##  
## Summary of the fixed effects for the species:  
##  
## Summary for Perca_fluviatilis:  
##  
##  
## Perca_fluviatilis_SCI -0.1655086 0.03767079 -0.2393420 -0.1655086  
## Perca_fluviatilis_HFP 0.4070348 0.02382541 0.3603378 0.4070348  
## Perca_fluviatilis_intercept -20.8083805 0.59953475 -21.9834471 -20.8083805  
## 0.975quant mode kld  
## Perca_fluviatilis_SCI -0.09167519 -0.1655086 0  
## Perca_fluviatilis_HFP 0.45373172 0.4070348 0  
## Perca_fluviatilis_intercept -19.63331402 -20.8083805 0  
##  
## Summary for Salmo_trutta:  
##  
##  
## Salmo_trutta_SCI -0.08729355 0.02579891 -0.13785848 -0.08729355  
## Salmo_trutta_HFP -0.02717185 0.02348937 -0.07321018 -0.02717185  
## Salmo_trutta_intercept -5.97755402 0.12177908 -6.21623663 -5.97755402  
## 0.975quant mode kld  
## Salmo_trutta_SCI -0.03672862 -0.08729355 0  
## Salmo_trutta_HFP 0.01886647 -0.02717185 0  
## Salmo_trutta_intercept -5.73887140 -5.97755402 0  
##  
## Summary for Salvelinus_alpinus:  
##  
##  
## Salvelinus_alpinus_SCI -0.01679422 0.04723110 -0.1093655 -0.01679422  
## Salvelinus_alpinus_HFP -0.09236926 0.04618182 -0.1828840 -0.09236926  
## Salvelinus_alpinus_intercept -7.69231713 0.14105706 -7.9687839 -7.69231713  
## 0.975quant mode kld  
## Salvelinus_alpinus_SCI 0.07577704 -0.01679422 0  
## Salvelinus_alpinus_HFP -0.00185456 -0.09236926 0  
## Salvelinus_alpinus_intercept -7.41585037 -7.69231713 0  
##  
## Summary for Esox_lucius:  
##  
##  
## Esox_lucius_SCI -0.1741681 0.05166809 -0.2754357 -0.1741681  
## Esox_lucius_HFP 0.1831995 0.03101655 0.1224082 0.1831995  
## Esox_lucius_intercept -18.6636744 0.48615967 -19.6165299 -18.6636744  
## 0.975quant mode kld  
## Esox_lucius_SCI -0.07290055 -0.1741681 0  
## Esox_lucius_HFP 0.24399081 0.1831995 0  
## Esox_lucius_intercept -17.71081897 -18.6636744 0
```

```

## Time used:
##      Pre = 4.99, Running = 119, Post = 2.63, Total = 127
## Random effects:
##   Name      Model
##   Perca_fluviatilis_survey_spatial SPDE2 model
##   Salmo_trutta_survey_spatial SPDE2 model
##   Salvelinus_alpinus_survey_spatial SPDE2 model
##   Esox_lucius_survey_spatial SPDE2 model
##   Salvelinus_alpinus_artsobs_spatial Copy
##   Esox_lucius_artsobs_spatial Copy
##   Salmo_trutta_artsobs_spatial Copy
##   Perca_fluviatilis_artsobs_spatial Copy
##
## Model hyperparameters:
##                                     mean      sd 0.025quant 0.5quant
## Range for Perca_fluviatilis_survey_spatial 105.96 12.205     84.17    105.20
## Stdev for Perca_fluviatilis_survey_spatial  3.17  0.274      2.66     3.17
## Range for Salmo_trutta_survey_spatial       32.82  3.135     27.00    32.70
## Stdev for Salmo_trutta_survey_spatial        1.91  0.092      1.72     1.90
## Range for Salvelinus_alpinus_survey_spatial 27.43  3.295     21.62    27.21
## Stdev for Salvelinus_alpinus_survey_spatial  2.42  0.140      2.15     2.42
## Range for Esox_lucius_survey_spatial         85.36  8.910     68.78    85.04
## Stdev for Esox_lucius_survey_spatial          3.04  0.260      2.57     3.03
##                                     0.975quant mode
## Range for Perca_fluviatilis_survey_spatial 132.16 103.56
## Stdev for Perca_fluviatilis_survey_spatial  3.74  3.15
## Range for Salmo_trutta_survey_spatial       39.33  32.51
## Stdev for Salmo_trutta_survey_spatial        2.09  1.91
## Range for Salvelinus_alpinus_survey_spatial 34.57  26.70
## Stdev for Salvelinus_alpinus_survey_spatial  2.70  2.43
## Range for Esox_lucius_survey_spatial         103.81 84.66
## Stdev for Esox_lucius_survey_spatial          3.60  2.99
##
## Deviance Information Criterion (DIC) .....: NA
## Deviance Information Criterion (DIC, saturated) ....: NA
## Effective number of parameters .....: NA
##
## Watanabe-Akaike information criterion (WAIC) ....: 7.02e+40
## Effective number of parameters .....: 3.51e+40
##
## Marginal log-Likelihood: -33559.81
## is computed
## Posterior summaries for the linear predictor and the fitted values are computed
## (Posterior marginals needs also 'control.compute=list(return.marginals.predictor=TRUE)')
#saveRDS(ISDM, "results/ISDM.rds")

```

This model has the species specific spatial fields, but we also want a bias field that is shared across the species. We add this using \$addBias.

```

ISDMsetup$addBias("artsobs")
ISDMsetup$specifySpatial(Bias = 'artsobs',
                        prior.range = c(50, 0.01),
                        prior.sigma = c(1, 0.01))

```

```

ISDMbias <- fitISDM(ISDMsetup,
                      options = list(num.threads = 2,
                                    control.inla = list(int.strategy = 'eb',
                                                        cmin = 0,
                                                        strategy = 'gaussian'),
                                    safe = TRUE,
                                    inla.mode = 'experimental'))

summary(ISDMbias)

## Summary of 'bruSDM' object:
##
## inlabru version: 2.10.1
## INLA version: 24.02.20
##
## Types of data modelled:
##
## survey             Present absence
## artsobs            Present only
##
## Summary of the fixed effects for the species:
##
## Summary for Perca_fluviatilis:
##                               mean      sd 0.025quant 0.5quant
## Perca_fluviatilis_SCI -0.16547448 0.03966570 -0.24321783 -0.16547448
## Perca_fluviatilis_HFP  0.06411709 0.02442068  0.01625343  0.06411709
## Perca_fluviatilis_intercept -2.63891672 0.91573735 -4.43372895 -2.63891672
##                               0.975quant   mode kld
## Perca_fluviatilis_SCI -0.08773113 -0.16547448  0
## Perca_fluviatilis_HFP  0.11198075  0.06411709  0
## Perca_fluviatilis_intercept -0.84410449 -2.63891672  0
##
## Summary for Salmo_trutta:
##                               mean      sd 0.025quant 0.5quant
## Salmo_trutta_SCI     -0.05395268 0.03069208 -0.11410805 -0.05395268
## Salmo_trutta_HFP     -0.02822912 0.02480707 -0.07685008 -0.02822912
## Salmo_trutta_intercept 0.72238164 0.23724369  0.25739256  0.72238164
##                               0.975quant   mode kld
## Salmo_trutta_SCI    0.006202683 -0.05395268  0
## Salmo_trutta_HFP    0.020391839 -0.02822912  0
## Salmo_trutta_intercept 1.187370722 0.72238164  0
##
## Summary for Salvelinus_alpinus:
##                               mean      sd 0.025quant 0.5quant
## Salvelinus_alpinus_SCI -0.003478329 0.05234097 -0.1060648 -0.003478329
## Salvelinus_alpinus_HFP -0.119871809 0.04947812 -0.2168471 -0.119871809
## Salvelinus_alpinus_intercept -0.861152042 0.17983369 -1.2136196 -0.861152042
##                               0.975quant   mode kld
## Salvelinus_alpinus_SCI  0.09910809 -0.003478329  0
## Salvelinus_alpinus_HFP -0.02289648 -0.119871809  0
## Salvelinus_alpinus_intercept -0.50868449 -0.861152042  0
##
## Summary for Esox_lucius:
##                               mean      sd 0.025quant 0.5quant 0.975quant

```

```

## Esox_lucius_SCI      -0.1468163 0.05508409 -0.25477916 -0.1468163 -0.03885349
## Esox_lucius_HFP      0.1502823 0.03250031  0.08658288  0.1502823  0.21398176
## Esox_lucius_intercept -2.8764433 0.55287931 -3.96006680 -2.8764433 -1.79281973
##
##                                     mode kld
## Esox_lucius_SCI      -0.1468163   0
## Esox_lucius_HFP      0.1502823   0
## Esox_lucius_intercept -2.8764433   0

## Time used:
##     Pre = 5.67, Running = 737, Post = 2.89, Total = 746
## Random effects:
##   Name      Model
##   Perca_fluviatilis_survey_spatial SPDE2 model
##   Salmo_trutta_survey_spatial SPDE2 model
##   Salvelinus_alpinus_survey_spatial SPDE2 model
##   Esox_lucius_survey_spatial SPDE2 model
##   artsobs_biasField SPDE2 model
##   Salvelinus_alpinus_artsobs_spatial Copy
##   Esox_lucius_artsobs_spatial Copy
##   Salmo_trutta_artsobs_spatial Copy
##   Perca_fluviatilis_artsobs_spatial Copy
##
## Model hyperparameters:
##                                         mean      sd 0.025quant 0.5quant
## Range for Perca_fluviatilis_survey_spatial 271.900 38.564    206.900  268.250
## Stdev for Perca_fluviatilis_survey_spatial  2.346  0.305     1.809   2.324
## Range for Salmo_trutta_survey_spatial      235.369 29.225    182.782  233.681
## Stdev for Salmo_trutta_survey_spatial       0.674  0.116     0.473   0.664
## Range for Salvelinus_alpinus_survey_spatial 49.300  8.818    35.079   48.265
## Stdev for Salvelinus_alpinus_survey_spatial  1.893  0.152     1.611   1.886
## Range for Esox_lucius_survey_spatial        129.377 25.215    88.435  126.475
## Stdev for Esox_lucius_survey_spatial         2.583  0.260     2.126   2.565
## Range for artsobs_biasField                 139.508  9.438   122.018  139.132
## Stdev for artsobs_biasField                  6.043  0.364     5.367   6.029
##
##                                         0.975quant      mode
## Range for Perca_fluviatilis_survey_spatial 358.373 259.166
## Stdev for Perca_fluviatilis_survey_spatial  3.008  2.277
## Range for Salmo_trutta_survey_spatial       297.663 230.546
## Stdev for Salmo_trutta_survey_spatial        0.928  0.646
## Range for Salvelinus_alpinus_survey_spatial 69.632  45.758
## Stdev for Salvelinus_alpinus_survey_spatial  2.210  1.874
## Range for Esox_lucius_survey_spatial        187.283 120.050
## Stdev for Esox_lucius_survey_spatial         3.148  2.517
## Range for artsobs_biasField                 159.163 138.266
## Stdev for artsobs_biasField                  6.798  5.997
##
## Deviance Information Criterion (DIC) .....: -35184.24
## Deviance Information Criterion (DIC, saturated) ....: NA
## Effective number of parameters .....: -42474.51
##
## Watanabe-Akaike information criterion (WAIC) ....: 1.43e+09
## Effective number of parameters .....: 7.15e+08
##
## Marginal log-Likelihood: -26272.51

```

```

##  is computed
## Posterior summaries for the linear predictor and the fitted values are computed
## (Posterior marginals needs also 'control.compute=list(return.marginals.predictor=TRUE)')
#saveRDS(ISDMbias, "results/ISDMbias.rds")

```

Predictions and plots

Once the model has been fit, we can look at the predictions from the species-specific shared fields and the bias field.

First we create a plot to show the coefficients and the associated credibility intervals for the four different models considered. The estimates and standard errors for the four models are relatively similar.

```

makeData <- function(data, name) {

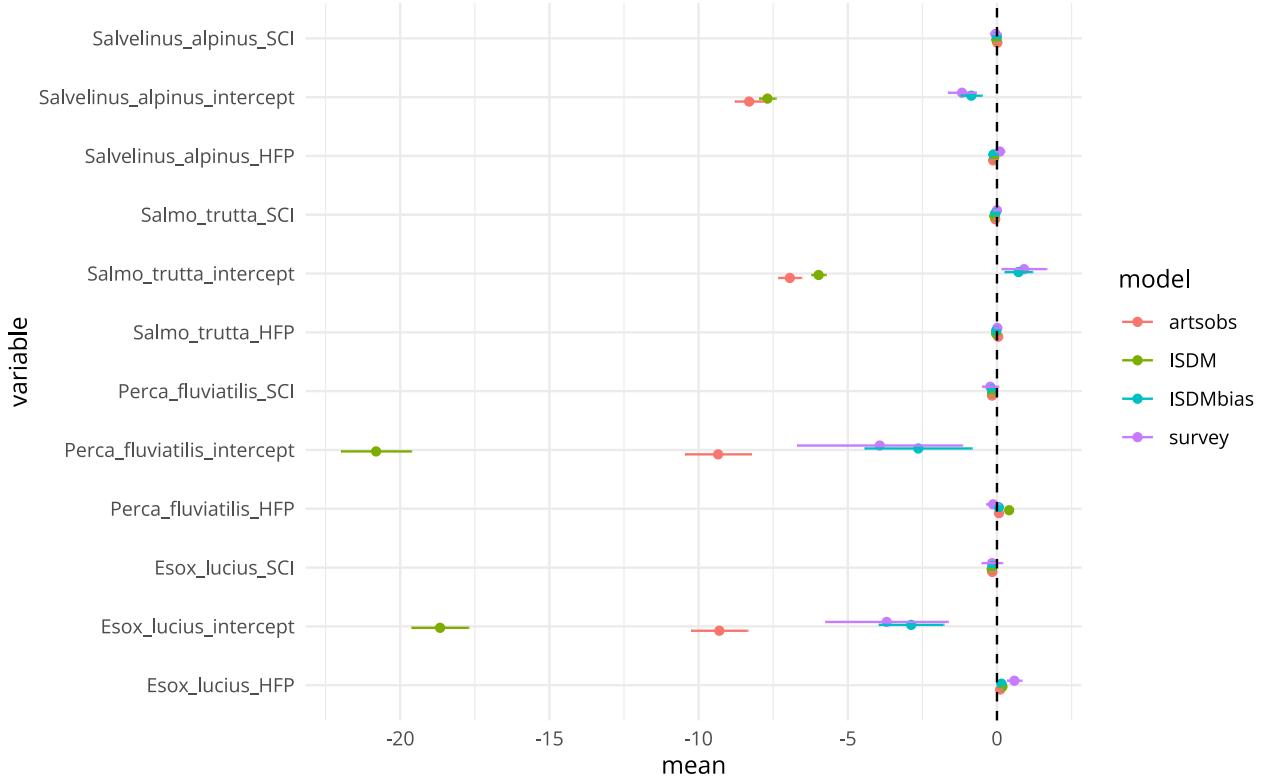
  data$summary.fixed$variable <- rownames(data$summary.fixed)
  data$summary.fixed$min <- data$summary.fixed$`0.025quant`
  data$summary.fixed$max <- data$summary.fixed$`0.975quant`
  data$summary.fixed$model <- name
  data$summary.fixed

}

plotData <- rbind(makeData(surveyFit, 'survey'),
                  makeData(artsobsFit, 'artsobs'),
                  makeData(ISDM, 'ISDM'),
                  makeData(ISDMbias, 'ISDMbias'))

ggplot(plotData, aes(x = mean, y = variable, col = model)) +
  geom_point(position=position_dodge(width=0.2)) +
  geom_errorbar(aes(x = mean, y = variable, xmin = min, xmax = max),
                position=position_dodge(width=0.2), width = 0) +
  geom_vline(xintercept = 0, lty = 2) +
  theme_minimal() +
  theme(text = element_text(family = f1),
        strip.text = element_text(family = f1, size = 12, face = "italic"),
        plot.tag = element_text(angle = 90, hjust = 0.5),
        plot.tag.position = c(-0.03, 0.45))

```



We define a function that will do species-specific predictions for the ISDM with a bias field, and save the species predictions, since these take a little time to compute.

```

predict_species <- function(model, species, predict_data){
  sharedfield <- predict(model,
    data = predict_data,
    spatial = TRUE,
    fun = 'linear',
    species = species,
    n.samples = 100)
  file_name <- paste0("results/sharedfield_", species, ".rds")
  saveRDS(sharedfield, file_name)
  return(sharedfield)
}

predData <- fm_pixels(mesh = mesh, mask = norway.poly, dims = c(450, 450))
prediction_list <- list()
for(fish in fishes) {
  prediction_list[[fish]] <- predict_species(
    model = ISDMbias,
    predict_data = predData,
    species = fish
  )
}

```

Once we have the predictions, we can make some plots. We similarly define a function that makes a plot for one species, and then run this for all four species.

```

NO <- st_boundary(st_as_sf(norway.poly))

plot_preferences <- list(scale_color_distiller(palette = "BrBG", direction = 1),

```

```

        coord_sf(),
        xlab(""),
        ylab(""),
        scale_x_continuous(breaks = c(5, 25)),
        scale_y_continuous(breaks = c(60, 68)),
        theme_minimal(),
        theme(text = element_text(family = f1),
              title = element_text(family = f1, size = 10, face = "italic"),
              legend.key.height = unit(0.3, "cm"),
              legend.title = element_blank(),
              legend.position = "bottom")
    )

plot_species <- function(predictions, species_to_plot, plot_preferences){

  p <- ggplot() +
    gg(predictions$speciesPredictions[[species_to_plot]],
       aes(col = mean)) +
    gg(NO, lwd = 0.8) +
    labs(title = sub("_", " ", species_to_plot)) +
    plot_preferences
  return(p)
}

plot_list <- list()
for(fish in fishes) {
  plot_list[[fish]] <- plot_species(
    predictions = readRDS(paste0("results/sharedfield_", fish, ".rds")),
    species = fish,
    plot_preferences = plot_preferences)
}

patchwork::wrap_plots(plot_list, nrow = 1)

  Esox lucius   Perca fluviatilis   Salmo trutta   Salvelinus alpinus

ggsave("figures/fishplot_four_species.pdf", height = 3*2, width = 8*2)
ggsave("figures/fishplot_four_species.png", height = 3*2, width = 8*2)


```

And finally we predict and plot the bias field, which is shared between all the fish, as it describes the human sampling more than the distribution of the fish.

```

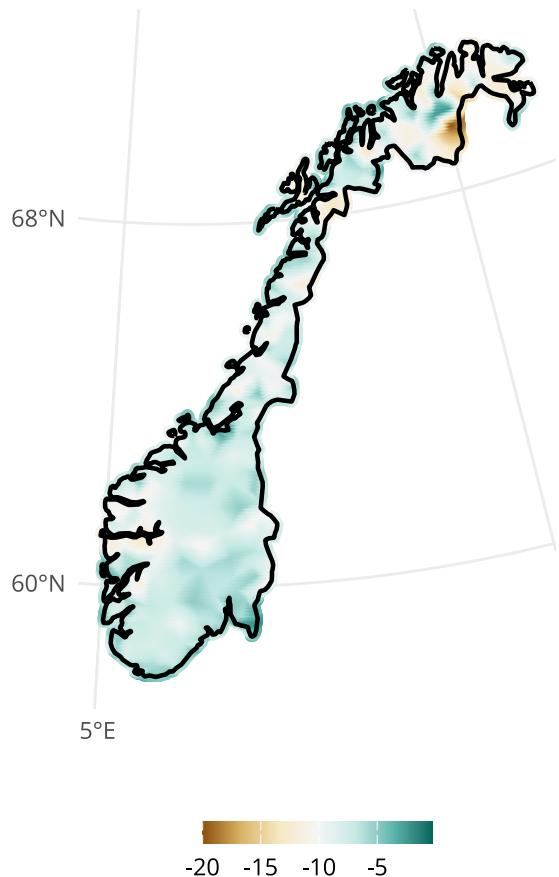
fish_biasfield <- predict(ISDMbias,
                           data = predData,
                           biasfield = TRUE,
                           fun = 'linear',
                           n.samples = 100)

saveRDS(fish_biasfield, "results/ISDMbiasfield.rds")
fish_biasfield <- readRDS("results/ISDMbiasfield.rds")

ggplot() +
  gg(fish_biasfield$biasFields$artsobs,
     aes(col = mean)) +
  gg(NO, lwd = 0.8) +
  labs(title = "Bias field") +
  plot_preferences

```

Bias field



```
ggsave("figures/ISDMbiasfield.pdf", width = 3*2, height = 3*2)
```

Session info and runtime

This document took 0.65 hours to compile.

Current session info

```

- Session info -----
setting  value
version  R version 4.3.3 (2024-02-29)
os       Ubuntu 20.04.1 LTS
system   x86_64, linux-gnu
ui       X11
language (EN)
collate  C.UTF-8
ctype    C.UTF-8
tz       Europe/Oslo
date     2024-04-08
pandoc   2.5 @ /usr/bin/ (via rmarkdown)

- Packages -----
package      * version    date (UTC) lib source
base64enc    0.1-3      2015-07-28 [1] CRAN (R 4.3.2)
blockCV       3.1-3      2023-06-04 [1] CRAN (R 4.3.1)
class         7.3-21     2023-01-23 [1] CRAN (R 4.2.2)
classInt      0.4-7      2022-06-10 [1] CRAN (R 4.2.1)
cli          3.6.1      2023-03-23 [1] CRAN (R 4.3.1)
clipr         0.8.0      2022-02-22 [1] CRAN (R 4.3.2)
codetools     0.2-19     2023-02-01 [1] CRAN (R 4.3.1)
colorspace    2.0-3      2022-02-21 [1] CRAN (R 4.1.2)
curl          4.3.3      2022-10-06 [1] CRAN (R 4.2.2)
DBI           1.2.2      2024-02-16 [1] CRAN (R 4.3.3)
desc          1.4.3      2023-12-10 [1] CRAN (R 4.3.2)
details       0.3.0      2022-03-27 [1] CRAN (R 4.3.2)
digest        0.6.31     2022-12-11 [1] CRAN (R 4.2.2)
dplyr         * 1.1.3     2023-09-03 [1] CRAN (R 4.3.1)
e1071         1.7-11     2022-06-07 [1] CRAN (R 4.2.1)
evaluate      0.23       2023-11-01 [1] CRAN (R 4.3.2)
fansi          1.0.2      2022-01-14 [1] CRAN (R 4.1.2)
farver         2.1.1      2022-07-06 [1] CRAN (R 4.2.1)
fastmap        1.1.1      2023-02-24 [1] CRAN (R 4.3.1)
fmesher        * 0.1.5     2023-12-20 [1] CRAN (R 4.3.2)
foreign        0.8-86     2023-11-28 [1] CRAN (R 4.3.2)
generics       0.1.3      2022-07-05 [1] CRAN (R 4.3.2)
ggplot2        * 3.5.0     2024-02-23 [1] CRAN (R 4.3.3)
glue           1.6.2      2022-02-24 [1] CRAN (R 4.2.1)
gtable          0.3.4      2023-08-21 [1] CRAN (R 4.3.1)
highr           0.10       2022-12-22 [1] CRAN (R 4.3.2)
htmltools      0.5.4      2022-12-07 [1] CRAN (R 4.2.2)
httr            1.4.7      2023-08-15 [1] CRAN (R 4.3.1)
INLA           * 24.02.20   2024-02-19 [1] local
inlabru        * 2.10.1     2023-12-21 [1] CRAN (R 4.3.2)
jsonlite        1.7.3      2022-01-17 [1] CRAN (R 4.1.2)
KernSmooth     2.23-22    2023-07-10 [1] CRAN (R 4.3.1)
knitr           1.45       2023-10-30 [1] CRAN (R 4.3.2)
labeling        0.4.3      2023-08-29 [1] CRAN (R 4.3.1)
lattice         0.20-45    2021-09-22 [1] CRAN (R 4.2.1)
lifecycle      1.0.4      2023-11-07 [1] CRAN (R 4.3.2)
magrittr       2.0.2      2022-01-26 [1] CRAN (R 4.1.2)
mapproj         * 1.2.8     2022-01-12 [1] CRAN (R 4.1.2)

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maps	* 3.4.0	2021-09-25	[1]	CRAN	(R 4.1.2)
maptools	1.1-3	2022-03-08	[1]	CRAN	(R 4.1.2)
Matrix	* 1.4-0	2021-12-08	[1]	CRAN	(R 4.1.2)
MatrixModels	0.5-0	2021-03-02	[1]	CRAN	(R 4.2.1)
mnormt	2.1.0	2022-06-07	[1]	CRAN	(R 4.2.1)
munsell	0.5.0	2018-06-12	[1]	CRAN	(R 4.3.2)
numDeriv	2016.8-1.1	2019-06-06	[1]	CRAN	(R 4.3.2)
patchwork	* 1.2.0	2024-01-08	[1]	CRAN	(R 4.3.2)
pillar	1.9.0	2023-03-22	[1]	CRAN	(R 4.3.1)
pkgconfig	2.0.3	2019-09-22	[1]	CRAN	(R 4.3.2)
plyr	1.8.8	2022-11-11	[1]	CRAN	(R 4.2.2)
png	0.1-8	2022-11-29	[1]	CRAN	(R 4.2.2)
PointedSDMs	* 1.3	2024-03-25	[1]	Github	(PhilipMostert/PointedSDMs@a3cd7a0)
proxy	0.4-27	2022-06-09	[1]	CRAN	(R 4.2.1)
R.devices	2.17.2	2024-01-29	[1]	CRAN	(R 4.3.2)
R.methodsS3	1.8.2	2022-06-13	[1]	CRAN	(R 4.3.2)
R.oo	1.26.0	2024-01-24	[1]	CRAN	(R 4.3.2)
R.utils	2.12.3	2023-11-18	[1]	CRAN	(R 4.3.2)
R6	* 2.5.1	2021-08-19	[1]	CRAN	(R 4.3.2)
ragg	1.2.7	2023-12-11	[1]	CRAN	(R 4.3.2)
raster	* 3.5-11	2021-12-23	[1]	CRAN	(R 4.1.2)
RColorBrewer	1.1-3	2022-04-03	[1]	CRAN	(R 4.3.2)
Rcpp	1.0.8	2022-01-13	[1]	CRAN	(R 4.1.2)
rlang	1.1.1	2023-04-28	[1]	CRAN	(R 4.3.1)
rmarkdown	2.25	2023-09-18	[1]	CRAN	(R 4.3.1)
scales	1.3.0	2023-11-28	[1]	CRAN	(R 4.3.2)
sessioninfo	1.2.2	2021-12-06	[1]	CRAN	(R 4.3.2)
sf	* 1.0-9	2022-11-08	[1]	CRAN	(R 4.2.2)
showtext	* 0.9-6	2023-05-03	[1]	CRAN	(R 4.3.1)
showtextdb	* 3.0	2020-06-04	[1]	CRAN	(R 4.3.1)
sn	2.1.1	2023-04-04	[1]	CRAN	(R 4.3.1)
sp	* 2.0-0	2023-06-22	[1]	CRAN	(R 4.3.1)
sysfonts	* 0.8.8	2022-03-13	[1]	CRAN	(R 4.3.1)
systemfonts	1.0.5	2023-10-09	[1]	CRAN	(R 4.3.1)
terra	1.6-47	2022-12-02	[1]	CRAN	(R 4.2.2)
textshaping	0.3.7	2023-10-09	[1]	CRAN	(R 4.3.1)
tibble	3.2.1	2023-03-20	[1]	CRAN	(R 4.3.1)
tidyselect	1.2.1	2024-03-11	[1]	CRAN	(R 4.3.3)
tinytex	0.49	2023-11-22	[1]	CRAN	(R 4.3.2)
units	0.8-0	2022-02-05	[1]	CRAN	(R 4.1.2)
utf8	1.2.2	2021-07-24	[1]	CRAN	(R 4.2.1)
vctrs	0.6.4	2023-10-12	[1]	CRAN	(R 4.3.1)
withr	3.0.0	2024-01-16	[1]	CRAN	(R 4.3.2)
xfun	0.40	2023-08-09	[1]	CRAN	(R 4.3.1)
xml2	1.3.3	2021-11-30	[1]	CRAN	(R 4.1.2)
yaml	2.3.7	2023-01-23	[1]	CRAN	(R 4.2.2)

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[1] /home/ahomec/p/philism/R/x86_64-pc-linux-gnu-library/4.1
[2] /usr/local/lib/R/site-library
[3] /usr/lib/R/site-library
[4] /usr/lib/R/library
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