Spatio-temporal

Philip S. Mostert

2024-06-17

This vignette is dedicated to illustrating a spatio-temporal ISDM analysis using the *PointedSDMs R* package. The analysis presented here is loosely adapted from a similar analysis presented in (Seaton, Jarvis, and Henrys 2024).

We aim to estimate maps of log-intensity across time for *Pyronia tithonus* (common name: *Gatekeeper*) across England, Scotland and Wales. Two datasets are considered: the *UK butterfly monitoring scheme* (*ukbms*), which are collected at regularly surveyed transects across the UK. The data comes in the form of an abundance dataset, however for this analysis we treated them as detection/non-detection data. The other dataset considered came from the *British Trust for Ornithology plus partner organisations* (*bto*). These data are collected by citizen scientists, and we therefore treated them as presence only data.

We load the packages required by the vignette:

```
library(sf)
```

```
## Linking to GEOS 3.11.0, GDAL 3.5.3, PROJ 9.1.0; sf_use_s2() is TRUE
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(tidyr)
library(ggplot2)
library(INLA)
```

```
## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

## Loading required package: sp

## This is INLA_24.03.20 built 2024-03-20 07:45:18 UTC.
##  - See www.r-inla.org/contact-us for how to get help.
##  - List available models/likelihoods/etc with inla.list.models()
##  - Use inla.doc(<NAME>) to access documentation
```

```
library(PointedSDMs)
```

```
## Loading required package: inlabru

## Loading required package: fmesher

## Loading required package: R6
```

And define a coordinate reference system to be used:

```
km_projection <- "+proj=tmerc +lat_0=49 +lon_0=-2 +k=0.9996012717 +x_0=400000 +y_0=-100000 +ellps=airy +
```

The data used in this analysis contains information from the year 2000 all the way to the year 2018. Estimating a model with too many time periods may take a long time to estimate. Therefore the time periods considered may be filtered using the following script. Note that estimating a model with three time periods as chosen here may still take a long while to estimate.

```
yearBegin <- 2006 #2000
yearEnd <- 2008 #2018
```

We next load in the data used in the analysis, and a *sf* object for the study region, which has been simplified slightly in order to produce a better mesh:

```
ukbms <- readRDS(file = 'Data/Vignette_temporal/ukbms.rds')
```

```
bto <- readRDS(file = 'Data/Vignette_temporal/bto.rds')
```

```
gb <- readRDS(file = 'Data/Vignette_temporal/gb.rds')
```

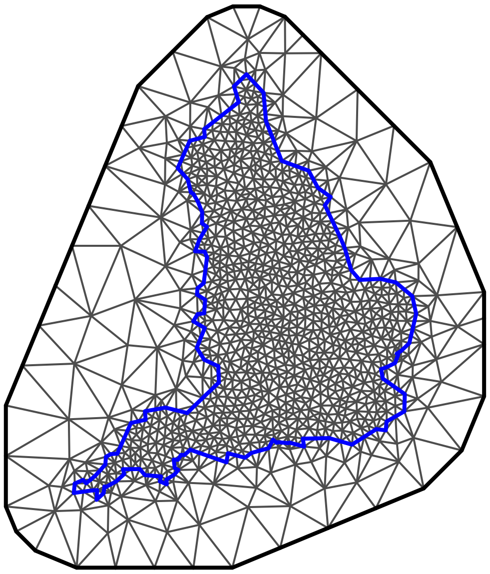
We then subset the data based on the chosen years.

```
ukbms <- ukbms %>%
  filter(Year >= yearBegin & Year <= yearEnd)

bto <- bto %>%
  filter(Year >= yearBegin & Year <= yearEnd)
```

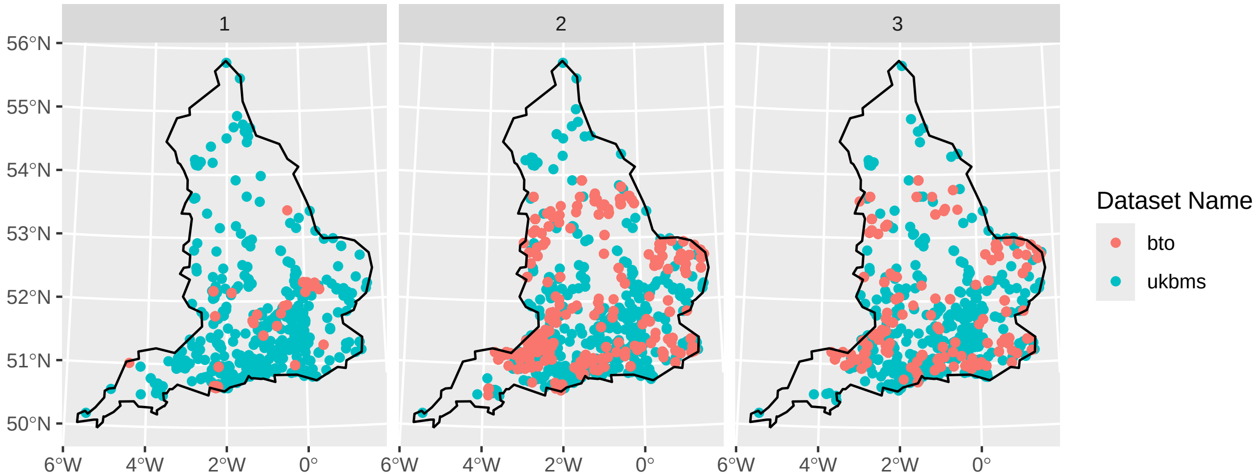
An *inla.mesh* object is created to estimate the spatial effect. We use a coarse mesh to speed up the run time of the models.

```
mesh <- inla.mesh.2d(boundary = INLA::inla.sp2segment(gb),
                     max.edge = c(5,30) * 4,
                     cutoff = 2,
                     offset = 2,
                     crs = km_projection)
plot(mesh)
```



We set up the model using the function `startISDM`, and specify the argument *temporalName* to set up a temporal analysis. The argument is the name of the column which contains information on the temporal variable, and is required to be standardized across datasets. We create a plot of the data to see how the data is spread across the map.

```
model_setup <- startISDM(ukbms, bto,
                         Projection = km_projection, Mesh = mesh,
                         Boundary = gb, responsePA = 'Presence',
                         temporalName = 'Year')
plot(model_setup)
```



A second spatial effect is added to the *bto* dataset to account for the spatial biases inherent in these data.

```
model_setup$addBias(datasetNames = 'bto')

## Turning copyModel off since the number of datasets specified is less than 2.
```

Priors for the spatial effects and the hyperparameters of the model are then set.

```
model_setup$specifySpatial(sharedSpatial = TRUE,
                           prior.range = c(100, 0.01),
                           prior.sigma = c(5, 0.01))
```

```r
model_setup$specifySpatial(Bias = TRUE,
                           prior.range = c(100, 0.01),
                           prior.sigma = c(5, 0.01))

ar1_hyper <- list(model = 'ar1', hyper = list(theta1 = list(prior = "pc.prec",
                                                             param = c(0.25, 0.01)),
                                  rho = list(prior = "pc.cor1",
                                             param = c(0.8, 0.8))))

model_setup$specifyRandom(temporalModel = ar1_hyper)
```

Estimation of the model may be completed `fitISDM`.

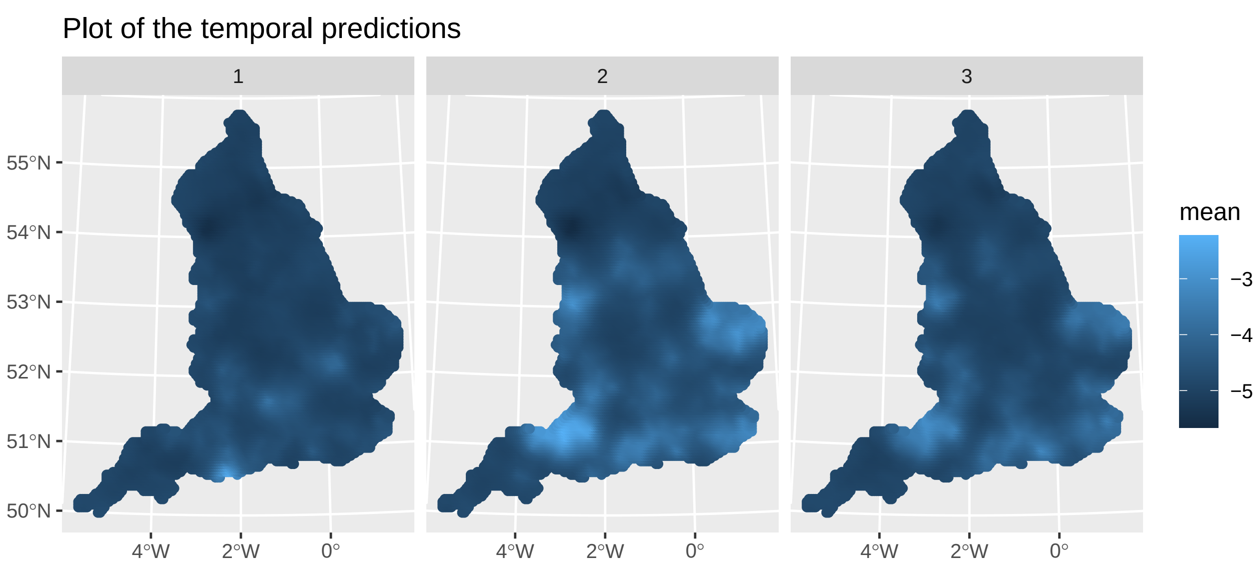
```r
TempModel <- fitISDM(model_setup, options = list(num.threads =2,
                                  verbose = TRUE,
                                  control.inla = list(
                                  int.strategy = 'eb',
                                  strategy = "adaptive",
                                  diagonal = 1)))
summary(TempModel)
```

```
## inlabru version: 2.10.1
## INLA version: 24.03.20
## Components:
## ukbms_spatial: main = spde(geometry), group = ar1(Year), replicate = iid(1L)
## bto_spatial(=ukbms_spatial): main = unknown(geometry), group = ar1(Year), replicate = iid(1L)
## ukbms_intercept: main = linear(1), group = exchangeable(1L), replicate = iid(1L)
## bto_intercept: main = linear(1), group = exchangeable(1L), replicate = iid(1L)
## bto_biasField: main = spde(geometry), group = ar1(Year), replicate = iid(1L)
## Likelihoods:
##   Family: 'binomial'
##     Data class: 'sf', 'data.frame'
##     Predictor: Presence ~ .
##   Family: 'cp'
##     Data class: 'sf', 'data.frame'
##     Predictor: geometry ~ .
## Time used:
##     Pre = 1.11, Running = 1066, Post = 0.655, Total = 1068
## Fixed effects:
##                   mean    sd 0.025quant 0.5quant 0.975quant   mode kld
## ukbms_intercept  0.968 0.039      0.891    0.968      1.045  0.968   0
## bto_intercept   -5.639 0.036     -5.710   -5.639     -5.569 -5.639   0
##
## Random effects:
##   Name     Model
##     ukbms_spatial SPDE2 model
##    bto_biasField SPDE2 model
##    bto_spatial Copy
##
## Model hyperparameters:
##                             mean    sd 0.025quant 0.5quant 0.975quant   mode
## Range for ukbms_spatial    65.485 7.936     50.469   65.272     81.614 65.472
## Stdev for ukbms_spatial     0.134 0.010      0.115    0.133      0.155  0.132
## GroupRho for ukbms_spatial  0.490 0.066      0.356    0.492      0.616  0.492
```

```
## Range for bto_biasField    42.471 3.041     36.842   42.348     48.809 42.072
## Stdev for bto_biasField     0.499 0.021      0.459    0.498      0.543  0.497
## GroupRho for bto_biasField  0.518 0.048      0.421    0.519      0.609  0.520
## Beta for bto_spatial        2.755 0.183      2.388    2.757      3.109  2.766
##
## Deviance Information Criterion (DIC) ...............: -44084.20
## Deviance Information Criterion (DIC, saturated) ....: NA
## Effective number of parameters .....................: -49496.97
##
## Watanabe-Akaike information criterion (WAIC) ...: 8884.89
## Effective number of parameters .................: 1830.75
##
## Marginal log-Likelihood:  -29150.87
##  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)')
```

And finally we create temporal predictions of the model using `predict`,

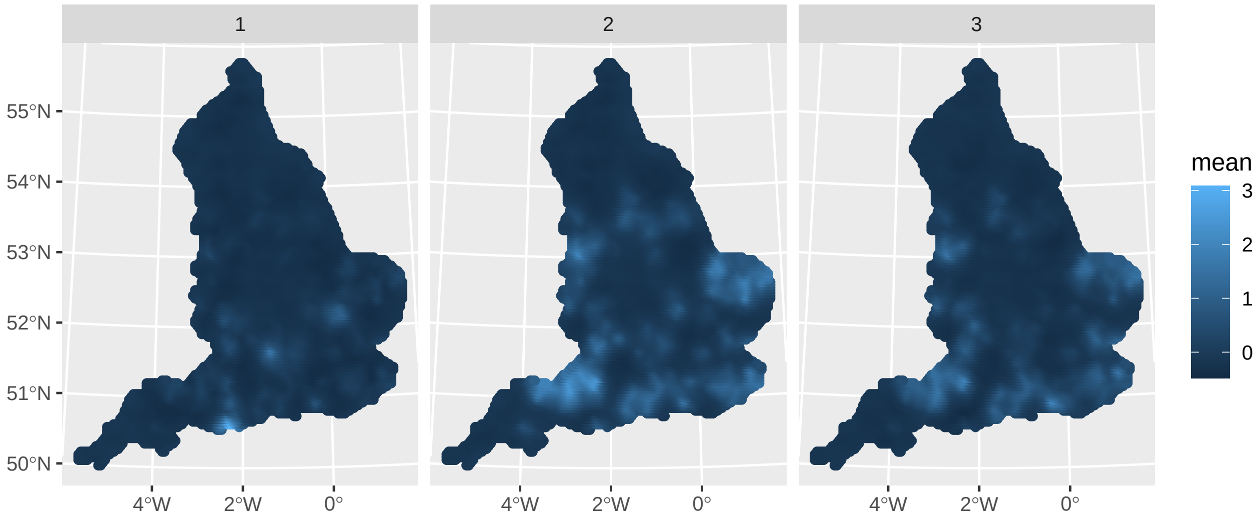
```r
pred <- predict(TempModel, mesh = mesh,
                mask = gb, predictor = TRUE)
plot(pred)
```



And temporal predictions of the bias component in a similar fashion.

```r
predBias <- predict(TempModel, mesh = mesh,
                    mask = gb, bias = TRUE)
plot(predBias)
```

Plot of the temporal predictions



Seaton, Fiona M., Susan G. Jarvis, and Peter A. Henrys. 2024. "Spatio-Temporal Data Integration for Species Distribution Modelling in R-INLA." *Methods in Ecology and Evolution*, May. https://doi.org/10.1111/2041-210x.14356.