Spatial Bayesian distributed lag non-linear models (SB-DLNM) with R-INLA

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In a recent paper published in this journal,[1] we introduced spatial Bayesian distributed lag non-linear models (SB-DLNMs) as a novel framework for estimating the short-term lagged health effects of environmental exposures in small areas. We extended the state-of-the-art approach for exposure-lag-response epidemiological modelling, distributed lag non-linear models (DLNMs),[2] by incorporating spatial models within a single-stage Bayesian framework to account for spatial dependence in risks. To evidence the practicality of SB-DLNMs, we conducted a case study estimating temperature-lag-mortality relationships in the 73 neighbourhoods of Barcelona. SB-DLNMs can be implemented using various Bayesian statistical software tools. We used WinBUGS for its flexibility in specifying complex hierarchical Bayesian models.[3] However, besides the need of conducting simulation studies that validates the robustness of the models, we acknowledged in the original paper that the biggest limitation of SB-DLNMs is their long execution times and high computational demands. As an alternative, R-INLA, based on integrated nested Laplace approximations,[4] offers faster computation compared to software alternatives using Markov chain Monte Carlo (MCMC),[5] such as WinBUGS. In this letter, we present the implementation of SB-DLNMs with R-INLA providing the illustrative code to reproduce the results of the same case study of small-area temperature-mortality associations in the Supplementary Text S1 and in a GitHub repository (https://github.com/marcosqz/sbdlnm_rinla_implementation).

The complete formulation of SB-DLNMs is detailed in the original SB-DLNM paper.[1] The approach involves considering the spatial arrangement of the data by assuming spatial distribution for the coefficients that define the exposure-lag-response association. This concept is feasible in R-INLA by using pre-implemented spatial models within the package.[6] Moreover, the flexibility inherent in Bayesian models is maintained in R-INLA by sampling from the joint posterior distribution using the function "*inla.posterior.sample*" in R.[6]

We executed both implementations of SB-DLNMs for the case study. In the new R-INLA implementation, each cross-basis coefficient has independent BYM2 spatial models,[7] whereas in the WinBUGS implementation, all Leroux spatial models share a common parameter. These changes are motivated by R-INLA's own limitations and in order to set, in our opinion, a good practical guidance for potential R-INLA users of this methodology. Nevertheless, the results obtained with the new R-INLA implementation are comparable to those presented in the original case study using the WinBUGS implementation (Figure 1 and Supplementary Figure S1). Both approaches give similar regional cumulative temperature-mortality associations and a consistent spatial distribution of heat-related mortality risks. The most notable finding however consists in the reduction in execution time for SB-DLNMs, from approximately two weeks in the original WinBUGS implementation to just 25 minutes with R-INLA in the case-crossover design (Figure 1).

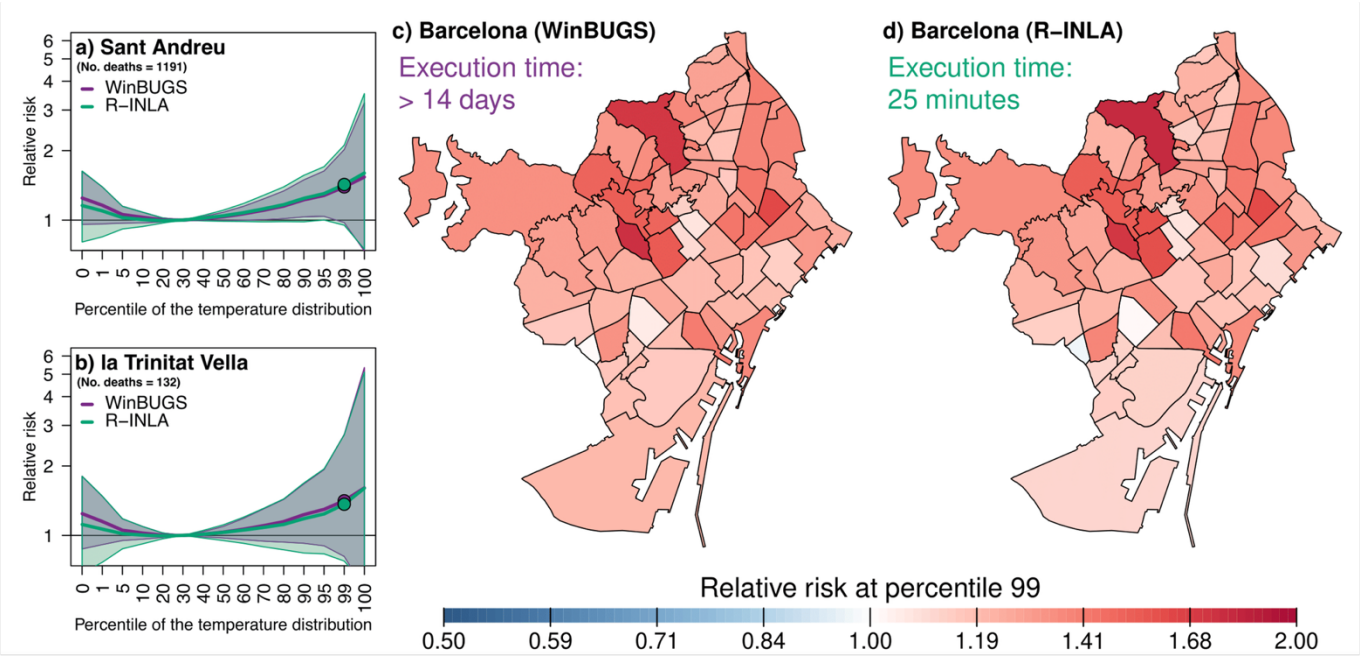

Figure 1: ***Overall cumulative temperature-mortality association in two adjacent neighbourhoods and spatial distribution of heat-related mortality risks in Barcelona (2007-2016) for WinBUGS and R-INLA implementations of spatial Bayesian distributed lag non-linear models (SB-DLNMs) with the case-crossover design****. Panels (a) and (b) show the association between the percentile of the neighbourhood*

temperature distribution and the relative risk of mortality. Curves are centred at the 30th percentile of the neighbourhood temperature distribution in both neighbourhoods. The thick curves represent the points estimates (ie median values) and the coloured areas represent the 95% credible interval of the estimates. Panels (c) and (d) show the point estimates of the relative risk of death at the 99th percentile of the neighbourhood temperature distribution, compared with the risk at the centring temperature in the 30th percentile, for the WinBUGS and R-INLA implementations respectively. Alt text: Graphs show small differences in the estimation of temperature-mortality associations between spatial Bayesian distributed lag non-linear models run in WinBUGS and R-INLA, but large differences in execution time.

In general, Table 1 shows the significantly faster execution times achieved with R-INLA compared to WinBUGS. The shift from several days to only a few seconds or minutes in the independent Bayesian DLNMs (B-DLNMs) shows the potential for implementing these models in single-location analyses. We note that the relative improvement in the execution times are higher in the case-crossover design than in the time-series design, though refining the R-INLA implementation or relaxing assumptions in the seasonality splines could narrow this gap.

MODEL	DESIGN	EXECUTION TIME WinBUGS	EXECUTION TIME R-INLA	RATIO EXECUTION TIME WinBUGS / R-INLA
Independent B-DLNM	Case-crossover	>2 days	59 seconds	~ 3.000
Independent B-DLNM	Time-series	>3 days	43 minutes	~ 100
SB-DLNM	Case-crossover	>14 days	25 minutes	~ 800
SB-DLNM	Time-series	>14 days	2.4 days	~ 6

*Table 1: **Execution times of the case-study of small-area temperature-associations for the WinBUGS and R-INLA implementations of independent Bayesian distributed lag non-linear models (B-DLNMs) and spatial Bayesian distributed lag non-linear models (SB-DLNMs)**. The models were run on a desktop computer with an Intel(R) Xeon(R) Gold 6230 CPU 2.10GHz processor (12 threads used in WinBUGS, 10 threads for R-INLA), and 64GB of RAM. The case-study models the short-term associations between temperature and mortality during the summer months (June-September) in 73 small-areas of Barcelona (2007-2016). The dataset included 39,569 deaths, with 19 (1,454) deaths in the neighbourhood with the lowest (highest) number of deaths. Distributed lag non-linear models modelling choices were based on previous studies, and specified in the original SB-DLNM paper.[1] Execution times could vary depending on many factors such as the specification of the models, the convergence criteria and the number of iterations in WinBUGS, the integration method and the approximation method for the posterior marginals in R-INLA. However, the importance of these results lies in the large differences in the magnitudes of the execution times.*

To extend the applicability range of SB-DLMNs to larger range of case studies, it was necessary to improve the implementation from the original SB-DLNM paper.[1] We achieved this by rewriting SB-DLNMs in R-INLA, which significantly reduced execution times compared with the WinBUGS implementation. Despite some differences in model implementations, the results for this case study are almost identical. However, it is important to acknowledge that model specification in R-INLA can be less flexible. For example, specifying common parameters across all spatial models, which is straightforward in WinBUGS, become more complex in R-INLA. Additionally, R-INLA, as an inference tool, has its own limitations, such as being an approximation method to the posterior distribution (similar to MCMC). However, its increased speed compared to many MCMC algorithms strengthens its practicality and usability.

The new R-INLA implementation offers several advantages. In contrast to WinBUGS, R-INLA allows for easy implementation on Linux clusters, which facilitates the parallelisation of the model in high-performance computing systems. This R-INLA implementation could allow future studies to use SB-DLNMs in cases involving large-scale datasets,[5] facilitating more direct comparisons with other small-area approaches using more spatial units,[8] or continent-wide datasets representing the intersection of small groups of age, sex, cause of disease and/or comorbidities, as it is currently being developed within the framework of the EARLY-ADAPT project.[9] By providing the R-INLA reproducible code for the case study (Supplementary Text S1 and in https://github.com/marcosqz/sbdlnm_rinla_implementation), we aim to encourage other researchers to use SB-DLNMs for both small-area and large-scale environmental epidemiology.

Ethics approval

This study is based on a secondary analysis of administrative data, and does not contain any studies with human participants performed by any of the authors. Informed consent of individuals, or approval by a medical ethics board, was not required under national regulations.

Data availability

The mortality data underlying this article were gathered from the mortality registry of Barcelona, which draws on both the mortality registry of the Department of Health of Catalonia and the municipal population registry. Data will be shared upon request to the corresponding author with permission from both the Department of Health of Catalonia and the municipal population registry. The temperature data underlying this article were provided by VITO [https://vito.be/en] by permission. Temperature data will be shared on request to the corresponding author with permission of VITO.

Author contributions

M.Q-Z. and M.M-D. conceptualized the study. M.Q-Z. and M.M-D. performed the statistical analysis. M.Q-Z. wrote the original draft. All authors contributed to the study design, the interpretation of the results and the drafting of the manuscript.

Use of Artificial intelligence (AI) tools

AI was used to improve readability and English grammar.

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Conflict of interest

None declared.

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Text S1: R-INLA code for Bayesian and spatial Bayesian distributed lag non-linear models (B-DLNM and SB-DLNM) in the case study of small-area short-term associations between temperature and mortality in Barcelona.

In the original SB-DLNM paper (https://doi.org/10.1093/ije/dyae061) we provided the WinBUGS implementation of SB-DLNMs. While WinBUGS provides flexibility in specifying complex hierarchical Bayesian models, R-INLA is a faster and computationally efficient method.

We provide in a GitHub repository (https://github.com/marcosqz/sbdlnm_rinla_implementation) the R-INLA implementation of SB-DLNMs with all the necessary files to reproduce the analysis of the temperature-mortality association in small areas presented in the original SB-DLNM paper: the shapefile of the city of Barcelona, the exposure temperature data at the regional level, and daily mortality data re-simulated from the fitted model (not the original due to confidentiality restrictions). With this reproducible code is possible to replicate the entire process of SB-DLNMs in R-INLA.

Here, in the supplementary data, we show the three scripts in which the code is divided:

1. *01_data_preparation.R*. The first code is for data preparation, transforming the usual time-series datasets of temperature and mortality into data ready to use for SB-DLNMs.
2. *02_run_sbdlm.R*. The second code presents the model specification and execution of independent B-DLNMs and SB-DLNMs in R-INLA.
3. *03_plot_sbdlnm.R*. The last code shows how to handle the output from the models in this Bayesian context: build and plot the three-dimensional exposure-lag-response surfaces, the overall associations, and map the risks showing the spatial patterns.

```r
################################################################################
# IMPORTANT: THE MORTALITY DATA provided are simulated FROM MODEL 4 (SB-DLNM
# WITH TIME-SERIES DESIGN) IN THE ORIGINAL SB-DLNM PAPER
(https://doi.org/10.1093/ije/dyae061)
# due to confidentiality restrictions of the original dataset. Original data
# may be requested to the data owner (The Barcelona Public Health Agency) who
# should share them in similar terms than those applying to this study. The
# supplied mortality, with exactly the same structure than the original dataset,
# allows reproducing the code provided so that interested readers may run it as
# an example of use. However, the results from the original data are
# additionally supplied (input/result_inla folder). We provide here the
# implementation of B-DLNMs and SB-DLNMS in R-INLA, a significantly faster and
# user-friendly software compared to WinBUGS.
# We used R version 4.4.2 and INLA version 24.12.11
################################################################################

################################################################################
# In this R project we implement Bayesian and spatial Bayesian distributed
# lag non-Linear models (B-DLNM and SB-DLNM) for the case study of short-term
# associations between temperature and mortality in the city of Barcelona.
################################################################################

################################################################################
# CODE 1: DATA PREPARATION
# Data preparation: Transforming time-series temperature and mortality datasets
# for B-DLNMs and SB-DLNMs.
################################################################################

# Load libraries

library(sf)
library(spdep)
library(lubridate)
library(dlnm)

# Load data

load("input/daily_data.RData")
shapefile_bcn <- read_sf("input/shapefile_bcn.shp")

# Subset data to only summer months of 2007 to 2016

data <- subset(data, month(date) %in% 6:9)
data <- subset(data, year(date) %in% 2007:2016)

# Generate a list of spatial structure from the shapefile for use in INLA.
list_neig <- nb2mat(poly2nb(shapefile_bcn), style = "B")
save(list_neig, file = "output/list_neighbours.RData")

# Set variables defining the dlnm model

dlnm_var <- list(
  var_prc = c(0.50, 0.90),
  var_fun = "ns",
  max_lag = 8,
  lagnk = 2,
  n_reg = 73,
  n_coef = 12)

# Set variables for trend and seasonality

df_seas <- 4
df_trend_10years <- 1 # 1 df every 10 years to control for long-term trends
df_trend <- round(
  length(min(year(data$date)):max(year(data$date))) / df_trend_10years / 10) # Here
  we assume the time period for all regions is the same
rm(df_trend_10years)

dlnm_var$df_seas <- df_seas
dlnm_var$df_trend <- df_trend

rm(df_seas, df_trend)

```

```r
save(dlnm_var, file = "output/dlnm_configuration.RData")

# Create crossbasis for each region

# Ensure that the data is ordered by region to maintain alignment between
# crossbasis and regions
if(is.unsorted(data$region)) {
  stop("data needs to be ordered by region for the next loop")}

list_cb <- lapply(formatC(1:dlnm_var$n_reg, width = 2, flag = "0"),
    function(i_reg) {

      temp <- subset(data, region == i_reg,
                     select = c("temp", paste0("lag", 1:dlnm_var$max_lag)))

      temp_knots <- quantile(temp$temp, dlnm_var$var_prc, na.rm = TRUE)
      temp_boundary <- range(temp, na.rm = TRUE)

      cb <- crossbasis(temp,
                       argvar = list(fun = dlnm_var$var_fun,
                                     knots = temp_knots,
                                     Boundary.knots = temp_boundary),
                       arglag = list(fun = "ns",
                                     knots = logknots(dlnm_var$max_lag,
                                                      dlnm_var$lagnk),
                                     intercept = TRUE))

      cb

})
cb <- do.call(rbind, list_cb)
rm(list_cb)

# Create different objects for the case-crossover and time-series designs

data_cco <- data; cb_cco <- cb
data_ts <- data; cb_ts <- cb

rm(data, cb)

# PREPARE DATA FOR THE CASE-CROSSOVER DESIGN

# Create strata for the case-crossover
# (neighborhood - year - month - day of week)
data_cco$strata <- paste(data_cco$region,
                         year(data_cco$date),
                         formatC(month(data_cco$date), width = 2, flag = "0"),
                         wday(data_cco$date, week_start = 1),
                         sep = ":")

# We exclude stratums without cases as they do not contribute to the
# likelihood in the case-crossover design
keep <- sapply(split(data_cco$mort, data_cco$strata), sum)
keep <- data_cco$strata %in% names(keep[keep != 0])
data_cco <- data_cco[keep,]
cb_cco <- cb_cco[keep,]
rm(keep)

save(data_cco, file = "output/data_casecrossover.RData")
save(cb_cco, file = "output/crossbasis_casecrossover.RData")

# PREPARE DATA FOR THE TIME-SERIES DESIGN

# Define day of week and year
data_ts$day_of_week <- wday(data_ts$date, week_start = 1)
data_ts$year <- year(data_ts$date)

# Create the trend matrix

trend <- onebasis(data_ts$date, fun = "ns", df = dlnm_var$df_trend)

# Create the seasonality matrix

```

```r
# Ensure that the data is ordered by region and year to maintain alignment
# between seasonality and data
if(is.unsorted(order(data_ts$region, data_ts$year))) {
  stop("data needs to be ordered by region and year for the next loop")}

seas <- lapply(formatC(1:dlnm_var$n_reg, width = 2, flag = "0"),
 function(i_reg) {
   lapply(unique(year(data_ts$date)), function(i_year) {
     date <- subset(data_ts, region == i_reg & year(date) == i_year)$date
     seas <- onebasis(yday(date), fun = "ns", df = dlnm_var$df_seas)
     return(seas)
   })
 })
seas <- do.call(rbind, do.call(rbind, seas))

save(data_ts, file = "output/data_timeseries.RData")
save(cb_ts, file = "output/crossbasis_timeseries.RData")
save(trend, file = "output/trend_timeseries.RData")
save(seas, file = "output/seasonality_timeseries.RData")
```

```r
################################################################################
# IMPORTANT: THE MORTALITY DATA provided are simulated FROM MODEL 4 (SB-DLNM
# WITH TIME-SERIES DESIGN) IN THE ORIGINAL SB-DLNM PAPER
(https://doi.org/10.1093/ije/dyae061)
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# supplied mortality, with exactly the same structure than the original dataset,
# allows reproducing the code provided so that interested readers may run it as
# an example of use. However, the results from the original data are
# additionally supplied (input/result_inla folder). We provide here the
# implementation of B-DLNMs and SB-DLNMS in R-INLA, a significantly faster and
# user-friendly software compared to WinBUGS.
# We used R version 4.4.2 and INLA version 24.12.11
################################################################################

################################################################################
# In this R project we implement Bayesian and spatial Bayesian distributed
# lag non-Linear models (B-DLNM and SB-DLNM) for the case study of short-term
# associations between temperature and mortality in the city of Barcelona.
################################################################################

################################################################################
# CODE 2: RUN B-DLNMs AND SB-DLNMs
# Model specification and execution: independent B-DLNMs and SB-DLNMs in R and
# R-INLA with simulated mortality data.
################################################################################

# Load libraries
library(INLA)

# 10 threads were used to generate the results
# Use "inla.setOption("num.threads", 10)" only if your computer has at least
# 10 threads

# inla.setOption("num.threads", 10)

# Load data for case-crossover design
load("output/data_casecrossover.RData")
load("output/crossbasis_casecrossover.RData")

# Load data for time-series design
load("output/data_timeseries.RData")
load("output/crossbasis_timeseries.RData")
load("output/trend_timeseries.RData")
load("output/seasonality_timeseries.RData")

# Load spatial data structure and DLNM configuration
load("output/list_neighbours.RData")
load("output/dlnm_configuration.RData")

# For INLA implementation, add variables identifying different categories

# (1) Case-crossover
colnames(cb_cco) <- paste0("cb", 1:ncol(cb_cco))
data_cco <- cbind(data_cco, cb_cco) # Add cross-basis to the dataset
for (i in 1:dlnm_var$n_coef) {
  col_name <- paste0("id_cb", i)
  data_cco[[col_name]] <- as.numeric(data_cco$region) # One estimate per region for
  cb coefficients
}; rm(i, col_name)

# (2) Time-series
colnames(cb_ts) <- paste0("cb", 1:ncol(cb_ts)) # Add cross-basis to the dataset
data_ts <- cbind(data_ts, cb_ts)
for (i in 1:dlnm_var$n_coef) {
  col_name <- paste0("id_cb", i)
  data_ts[[col_name]] <- as.numeric(data_ts$region) # One estimate per region for cb
  coefficients
}; rm(i, col_name)

data_ts$trend <- trend[,1] # Add trend to the dataset
data_ts$id_trend <- as.numeric(data_ts$region)  # One estimate per region for trend
```

```r
coefficients

colnames(seas) <- paste0("seas", 1:dlnm_var$df_seas)
data_ts <- cbind(data_ts, seas) # Add seasonality to the dataset
for (i in 1:dlnm_var$df_seas) {
  data_ts[[paste0("id_year", i)]] <- lubridate::year(data_ts$date) # One estimate per year and region for seasonality coefficients
  data_ts[[paste0("id_region", i)]] <- as.numeric(data_ts$region)
}; rm(i)

data_ts$intercept_dow <- paste0("dow_", data_ts$day_of_week, "_", data_ts$region) # Add day of week to the dataset

#.....................................................................
### MODEL 1 (Independent B-DLNM - case-crossover design) ####
#.....................................................................

### INLA - MODEL 1 Independent B-DLNM - case-crossover design

inla_formula <- mort ~ -1 +
  f(strata, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb1, cb1, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb2, cb2, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb3, cb3, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb4, cb4, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb5, cb5, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb6, cb6, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb7, cb7, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb8, cb8, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb9, cb9, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb10, cb10, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb11, cb11, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb12, cb12, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE)))

# In order to sample from the posterior distribution model need to be fitted
# with config = TRUE
inla_model <- inla(inla_formula,
                   data = data_cco, family = "poisson",
                   control.compute = list(config = TRUE),
                   control.inla = list(strategy = "laplace",
                                       int.strategy = "grid"))

# Extract the ensemble of sample coefficients of the crossbasis
inla_res <- inla.posterior.sample(1000, inla_model,
                                  selection = list("id_cb1" = 1:dlnm_var$n_reg,
                                                   "id_cb2" = 1:dlnm_var$n_reg,
                                                   "id_cb3" = 1:dlnm_var$n_reg,
                                                   "id_cb4" = 1:dlnm_var$n_reg,
                                                   "id_cb5" = 1:dlnm_var$n_reg,
                                                   "id_cb6" = 1:dlnm_var$n_reg,
                                                   "id_cb7" = 1:dlnm_var$n_reg,
                                                   "id_cb8" = 1:dlnm_var$n_reg,
                                                   "id_cb9" = 1:dlnm_var$n_reg,
                                                   "id_cb10" = 1:dlnm_var$n_reg,
                                                   "id_cb11" = 1:dlnm_var$n_reg,
                                                   "id_cb12" = 1:dlnm_var$n_reg))

cb_res <- lapply(1:dlnm_var$n_reg, function(i_reg) {
  beta_reg <- sapply(inla_res, function(x) {
    sapply(1:dlnm_var$n_coef, function(i) {
```

```r
      x$latent[paste0("id_cb", i, ":", i_reg),]
    })
  })
  t(beta_reg)
})

# save(cb_res, file = "output/predicted_inla_model1_independent_casecrossover.RData")

rm(inla_formula, inla_model, inla_res, cb_res)

#.....................................................................
### MODEL 2 (Independent B-DLNM - time-series design) ####
#.....................................................................

### INLA - MODEL 2 Independent B-DLNM - time-series design

inla_formula <- mort ~ -1 +
  f(intercept_dow, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb1, cb1, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb2, cb2, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb3, cb3, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb4, cb4, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb5, cb5, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb6, cb6, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb7, cb7, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb8, cb8, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb9, cb9, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb10, cb10, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb11, cb11, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_cb12, cb12, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  f(id_trend, trend, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE))) +
  seas1:factor(id_year1):factor(id_region1) +
  seas2:factor(id_year2):factor(id_region2) +
  seas3:factor(id_year3):factor(id_region3) +
  seas4:factor(id_year4):factor(id_region4)

# In order to sample from the posterior distribution model need to be fitted
# with config = TRUE
inla_model <- inla(inla_formula,
                   data = data_ts, family = "poisson",
                   control.compute = list(config = TRUE),
                   control.inla = list(strategy = "laplace",
                                       int.strategy = "grid"))

# Extract the ensemble of sample coefficients of the crossbasis
inla_res <- inla.posterior.sample(1000, inla_model,
                                  selection = list("id_cb1" = 1:dlnm_var$n_reg,
                                                   "id_cb2" = 1:dlnm_var$n_reg,
                                                   "id_cb3" = 1:dlnm_var$n_reg,
                                                   "id_cb4" = 1:dlnm_var$n_reg,
                                                   "id_cb5" = 1:dlnm_var$n_reg,
                                                   "id_cb6" = 1:dlnm_var$n_reg,
                                                   "id_cb7" = 1:dlnm_var$n_reg,
                                                   "id_cb8" = 1:dlnm_var$n_reg,
                                                   "id_cb9" = 1:dlnm_var$n_reg,
                                                   "id_cb10" = 1:dlnm_var$n_reg,
                                                   "id_cb11" = 1:dlnm_var$n_reg,
                                                   "id_cb12" = 1:dlnm_var$n_reg))

```

```r
cb_res <- lapply(1:dlnm_var$n_reg, function(i_reg) {
  beta_reg <- sapply(inla_res, function(x) {
    sapply(1:dlnm_var$n_coef, function(i) {
      x$latent[paste0("id_cb", i, ":", i_reg),]
    })
  })
  t(beta_reg)
})

# save(cb_res, file = "output/predicted_inla_model2_independent_timeseries.RData")

rm(inla_formula, inla_model, inla_res, cb_res)

#.....................................................................
### MODEL 3 (SB-DLNM - case-crossover design) ####
#.....................................................................

### INLA - MODEL 3 SB-DLNM - case-crossover design

inla_formula <- mort ~ -1 +
  cb1 + cb2 + cb3 + cb4 + cb5 + cb6 +
  cb7 + cb8 + cb9 + cb10 + cb11 + cb12 +
  f(strata, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed = TRUE
  ))) +
  f(id_cb1, cb1, model = "bym2", graph = list_neig) +
  f(id_cb2, cb2, model = "bym2", graph = list_neig) +
  f(id_cb3, cb3, model = "bym2", graph = list_neig) +
  f(id_cb4, cb4, model = "bym2", graph = list_neig) +
  f(id_cb5, cb5, model = "bym2", graph = list_neig) +
  f(id_cb6, cb6, model = "bym2", graph = list_neig) +
  f(id_cb7, cb7, model = "bym2", graph = list_neig) +
  f(id_cb8, cb8, model = "bym2", graph = list_neig) +
  f(id_cb9, cb9, model = "bym2", graph = list_neig) +
  f(id_cb10, cb10, model = "bym2", graph = list_neig) +
  f(id_cb11, cb11, model = "bym2", graph = list_neig) +
  f(id_cb12, cb12, model = "bym2", graph = list_neig)

# In order to sample from the posterior distribution model need to be fitted
# with config = TRUE
inla_model <- inla(inla_formula,
                   data = data_cco, family = "poisson",
                   control.compute = list(config = TRUE),
                   control.inla = list(strategy = "laplace",
                                       int.strategy = "grid"))

# Extract the ensemble of sample coefficients of the crossbasis
inla_res <- inla.posterior.sample(1000, inla_model,
                                  selection = list(cb1 = 1,
                                                   cb2 = 1,
                                                   cb3 = 1,
                                                   cb4 = 1,
                                                   cb5 = 1,
                                                   cb6 = 1,
                                                   cb7 = 1,
                                                   cb8 = 1,
                                                   cb9 = 1,
                                                   cb10 = 1,
                                                   cb11 = 1,
                                                   cb12 = 1,
                                                   "id_cb1" = 1:dlnm_var$n_reg,
                                                   "id_cb2" = 1:dlnm_var$n_reg,
                                                   "id_cb3" = 1:dlnm_var$n_reg,
                                                   "id_cb4" = 1:dlnm_var$n_reg,
                                                   "id_cb5" = 1:dlnm_var$n_reg,
                                                   "id_cb6" = 1:dlnm_var$n_reg,
                                                   "id_cb7" = 1:dlnm_var$n_reg,
                                                   "id_cb8" = 1:dlnm_var$n_reg,
                                                   "id_cb9" = 1:dlnm_var$n_reg,
                                                   "id_cb10" = 1:dlnm_var$n_reg,
                                                   "id_cb11" = 1:dlnm_var$n_reg,
                                                   "id_cb12" = 1:dlnm_var$n_reg))

cb_res <- lapply(1:dlnm_var$n_reg, function(i_reg) {
```

```r
  beta_reg <- sapply(inla_res, function(x) {
    sapply(1:dlnm_var$n_coef, function(i) {
      x$latent[paste0("cb", i, ":1"),] +
        x$latent[paste0("id_cb", i, ":", i_reg),]
    })
  })
  t(beta_reg)
})

# save(cb_res, file = "output/predicted_inla_model3_spatial_casecrossover.RData")

rm(sdunif, inla_formula, inla_model, inla_res, cb_res)

#.....................................................................
### MODEL 4 (SB-DLNM - time-series design) ####
#.....................................................................

### INLA - MODEL 4 SB-DLNM - time-series design

inla_formula <- mort ~ -1 +
  cb1 + cb2 + cb3 + cb4 + cb5 + cb6 +
  cb7 + cb8 + cb9 + cb10 + cb11 + cb12 +
  f(intercept_dow, model = "iid", hyper = list(prec = list(initial = log(1e-04), fixed
   = TRUE))) +
  f(id_cb1, cb1, model = "bym2", graph = list_neig) +
  f(id_cb2, cb2, model = "bym2", graph = list_neig) +
  f(id_cb3, cb3, model = "bym2", graph = list_neig) +
  f(id_cb4, cb4, model = "bym2", graph = list_neig) +
  f(id_cb5, cb5, model = "bym2", graph = list_neig) +
  f(id_cb6, cb6, model = "bym2", graph = list_neig) +
  f(id_cb7, cb7, model = "bym2", graph = list_neig) +
  f(id_cb8, cb8, model = "bym2", graph = list_neig) +
  f(id_cb9, cb9, model = "bym2", graph = list_neig) +
  f(id_cb10, cb10, model = "bym2", graph = list_neig) +
  f(id_cb11, cb11, model = "bym2", graph = list_neig) +
  f(id_cb12, cb12, model = "bym2", graph = list_neig) +
  f(id_trend, trend, model = "iid", hyper = list(prec = list(initial = log(1e-04),
  fixed = TRUE))) +
  seas1:factor(id_year1):factor(id_region1) +
  seas2:factor(id_year2):factor(id_region2) +
  seas3:factor(id_year3):factor(id_region3) +
  seas4:factor(id_year4):factor(id_region4)

# In order to sample from the posterior distribution model need to be fitted
# with config = TRUE
inla_model <- inla(inla_formula,
                   data = data_ts, family = "poisson",
                   control.compute = list(config = TRUE),
                   control.inla = list(strategy = "laplace",
                                       int.strategy = "grid"))

# Extract the ensemble of sample coefficients of the crossbasis
inla_res <- inla.posterior.sample(1000, inla_model,
                                  selection = list(cb1 = 1,
                                                   cb2 = 1,
                                                   cb3 = 1,
                                                   cb4 = 1,
                                                   cb5 = 1,
                                                   cb6 = 1,
                                                   cb7 = 1,
                                                   cb8 = 1,
                                                   cb9 = 1,
                                                   cb10 = 1,
                                                   cb11 = 1,
                                                   cb12 = 1,
                                                   "id_cb1" = 1:dlnm_var$n_reg,
                                                   "id_cb2" = 1:dlnm_var$n_reg,
                                                   "id_cb3" = 1:dlnm_var$n_reg,
                                                   "id_cb4" = 1:dlnm_var$n_reg,
                                                   "id_cb5" = 1:dlnm_var$n_reg,
                                                   "id_cb6" = 1:dlnm_var$n_reg,
                                                   "id_cb7" = 1:dlnm_var$n_reg,
                                                   "id_cb8" = 1:dlnm_var$n_reg,
```

```
                                                    "id_cb9" = 1:dlnm_var$n_reg,
                                                    "id_cb10" = 1:dlnm_var$n_reg,
                                                    "id_cb11" = 1:dlnm_var$n_reg,
                                                    "id_cb12" = 1:dlnm_var$n_reg))

cb_res <- lapply(1:dlnm_var$n_reg, function(i_reg) {
  beta_reg <- sapply(inla_res, function(x) {
    sapply(1:dlnm_var$n_coef, function(i) {
      x$latent[paste0("cb", i, ":1"),] +
        x$latent[paste0("id_cb", i, ":", i_reg),]
    })
  })
  t(beta_reg)
})

# save(cb_res, file = "output/predicted_inla_model4_spatial_timeseries.RData")

rm(sdunif, inla_formula, inla_model, inla_res, cb_res)
```

```r
################################################################################
# IMPORTANT: THE MORTALITY DATA provided are simulated FROM MODEL 4 (SB-DLNM
# WITH TIME-SERIES DESIGN) IN THE ORIGINAL SB-DLNM PAPER
(https://doi.org/10.1093/ije/dyae061)
# due to confidentiality restrictions of the original dataset. Original data
# may be requested to the data owner (The Barcelona Public Health Agency) who
# should share them in similar terms than those applying to this study. The
# supplied mortality, with exactly the same structure than the original dataset,
# allows reproducing the code provided so that interested readers may run it as
# an example of use. However, the results from the original data are
# additionally supplied (input/result_inla folder). We provide here the
# implementation of B-DLNMs and SB-DLNMS in R-INLA, a significantly faster and
# user-friendly software compared to WinBUGS.
# We used R version 4.4.2 and INLA version 24.12.11
################################################################################

################################################################################
# In this R project we implement Bayesian and spatial Bayesian distributed
# lag non-Linear models (B-DLNM and SB-DLNM) for the case study of short-term
# associations between temperature and mortality in the city of Barcelona.
################################################################################

################################################################################
# CODE 3: PLOT SB-DLNMs
# Handling with output from SB-DLNMs: Construct and plot 3D surface associations,
# overall cumulative associations, and mapping spatial patterns in R.
################################################################################

# Load libraries

library(dlnm)
library(leaflet)
library(sf)
library(lubridate)

# Load necessary files

load("input/daily_data.RData")
shapefile_bcn <- read_sf("input/shapefile_bcn.shp")
# WARNING: WE LOAD THE OUTPUT FROM MODEL 3 EXECUTED WITH R-INLA AND THE
# REAL MORTALITY DATA. IT CAN BE REPLACED FOR ANY OF THE OTHER OUTPUTS OBTAINED
# WITH REAL DATA OR OBTAINED WITH THE PREDICTED DATA FROM CODE 02_run_sbdlm.R
load("input/result_inla/final_inla_model3_spatial_casecrossover.RData")
load("output/dlnm_configuration.RData")

# DATA PREPARATION

# Subset data to only summer months of 2007 to 2016

data <- subset(data, month(date) %in% 6:9)
data <- subset(data, year(date) %in% 2007:2016)

# Define the percentiles of temperature to be calculated
percentiles <- c(seq(0, 1, by = 0.1),
                 seq(2, 98, by = 1),
                 seq(99, 100, by = 0.1)) /100

# Create the temperature values used in the DLNM models
list_temp <- lapply(1:dlnm_var$n_reg, function(i_reg) {

  label_reg <- formatC(i_reg, width = 2, flag = "0")
  temp <- subset(data, region == label_reg,
                 select = c("temp", paste0("lag", 1:dlnm_var$max_lag)))
  temp_knots <- quantile(temp[["temp"]], dlnm_var$var_prc, na.rm = TRUE)
  temp_boundary <- range(temp, na.rm = TRUE)
  x_temp <- quantile(temp[["temp"]], percentiles, na.rm = TRUE)

  return(list(temp_knots = temp_knots, # knots of the exposure-response function
              temp_boundary = temp_boundary, # range of temperatures
              x_temp = x_temp)) # temperatures in which risk are calculated

})

```

```r
temp_knots <- sapply(list_temp, function(x) x[["temp_knots"]])
temp_boundary <- sapply(list_temp, function(x) x[["temp_boundary"]])
x_temp <- sapply(list_temp, function(x) x[["x_temp"]])
rm(list_temp)

# Create a list with the basis for exposure and the basis for lags
# in each neighbourhood

basis_all <- lapply(1:dlnm_var$n_reg, function(i_reg) {

  f.temp_knots <- temp_knots[,i_reg]
  f.temp_boundary <- temp_boundary[,i_reg]
  f.x_temp <- x_temp[,i_reg]

  # basis temperatures
  Q <- onebasis(f.x_temp, fun = dlnm_var$var_fun, knots = f.temp_knots,
                Boundary.knots = f.temp_boundary)

  # basis lags
  C <- onebasis(0:dlnm_var$max_lag, fun = "ns",
                knots = logknots(dlnm_var$max_lag, dlnm_var$lagnk),
                intercept = TRUE)

  return(list(basis_exp = Q, basis_lag = C))

})

# Create a list with the cross-basis in each neighbourhood

cb <- lapply(1:dlnm_var$n_reg, function(i_reg) {

  cb <- crossbasis(matrix(rep(x_temp[,i_reg], dlnm_var$max_lag + 1),
                          ncol = dlnm_var$max_lag + 1),
                   argvar = list(fun = dlnm_var$var_fun,
                                 knots = temp_knots[,i_reg],
                                 Boundary.knots = temp_boundary[,i_reg]),
                   arglag = list(fun = "ns",
                                 knots = logknots(dlnm_var$max_lag, dlnm_var$lagnk),
                                 intercept = TRUE))

  return(cb)

})

#-----------------------------------------------------------------
# A) PANEL 3-DIMENSIONAL TEMPERATURE-LAG-RISK ASSOCIATION
# FOR REGION 1 / ITERATION 1 (EQUIVALENT TO PANEL FIGURE 1 IN THE ORIGINAL SB-DLNM PAPER)
#-----------------------------------------------------------------

# Specify the neighborhood of Barcelona (any integer from 1 to 73)
i_reg <- 1

basis_exp <- basis_all[[i_reg]]$basis_exp
basis_lag <- basis_all[[i_reg]]$basis_lag
f.x_temp <- x_temp[,i_reg]

# Extract the ensemble of sample coefficients of the crossbasis
beta_reg <- cb_res[[i_reg]]

# Initialize the array to store the RR for each temperature and lag combination
cp <- array(NA, dim = c(nrow(beta_reg), length(f.x_temp), dlnm_var$max_lag + 1))

for(i_iter in 1:nrow(beta_reg)) {
  for(i_temp in 1:length(f.x_temp)) {
    for(i_lag in 1:(dlnm_var$max_lag + 1)) {
      cp[i_iter, i_temp, i_lag] <- sum(
        (t(basis_exp[i_temp,,drop = FALSE]) %*% basis_lag[i_lag,, drop = FALSE]) *
          matrix(beta_reg[i_iter,], ncol = ncol(basis_lag), byrow = TRUE))
    }
  }
}
rm(i_iter, i_temp, i_lag)
```

```r

# Position of the temperature percentile where we center the associations
i_cen <- percentiles == 0.3

# New array to store the centered association
cp_cen <- array(NA, dim = c(nrow(beta_reg), length(f.x_temp), dlnm_var$max_lag + 1))

for(i in 1:length(f.x_temp)){
  cp_cen[,i,] <- cp[,i,]-cp[,i_cen,]
}; rm(i, cp)

# Choose an iteration for plotting (e.g., the first iteration)
cp_plot <- exp(cp_cen[1,,])

# Plot three-dimensional associations
pdf("plot/figureA_exposure_lag_response_surface.pdf",
    width = 5, height = 5)
par(mex = 0.3)
association <-
  persp(x = f.x_temp, y = 0:dlnm_var$max_lag, z = cp_plot, border = NA,
        ticktype = "detailed", theta = 240, phi = 50,
        xlab = "\nTemperature (°C)", ylab = "\nLag (days)", zlab = "\nRelative risk",
        col = "lightskyblue", zlim = c(min(cp_plot), max(cp_plot)),
        ltheta = 170, shade = 0.75, r = sqrt(3), d = 5,
        cex.lab = 0.8, cex.axis = 0.8, main = "A) Exposure-lag-response surface")

# Add lines for risk at lag 1, risk at percentile 99, and centring temperature
lines(trans3d(x = f.x_temp, y = 1,
              z = cp_plot[,2],
              pmat = association), lwd = 2, col = "red")
lines(trans3d(x = f.x_temp[percentiles == 0.99], y = 0:dlnm_var$max_lag,
              z = cp_plot[percentiles == 0.99,],
              pmat = association), lwd = 2, col = "orange")
lines(trans3d(x = f.x_temp[i_cen], y = 0:dlnm_var$max_lag,
              z = cp_plot[i_cen,],
              pmat = association), lwd = 2, col = "black")

dev.off()

# Clean up variables
rm(i_reg, basis_exp, basis_lag, f.x_temp, beta_reg, cp_cen, i_cen, association,
   cp_plot)

#-----------------------------------------------------------------
### B) OVERALL CUMULATIVE TEMPERATURE-MORTALITY ASSOCIATION FOR REGION 1
### (EQUIVALENT TO FIGURE 2 IN THE ORIGINAL SB-DLNM PAPER)
#-----------------------------------------------------------------

# Specify the neighborhood of Barcelona (any integer from 1 to 73)
i_reg <- 1

# Extract the ensemble of sample coefficients of the crossbasis
beta_reg <- cb_res[[i_reg]]

# Calculate directly the RR of the overall cumulative temperature-mortality
# associations for region i_reg
rr <- apply(beta_reg, 1, function(x) {
  sapply(1:length(x_temp[,i_reg]), function(i) cb[[i_reg]][i,] %*% x)
})

# Keep the exposure variable for the region
x_plot <- x_temp[, 1]

# Center the curve
i_cen <- percentiles == 0.3
rr_plot <- t(apply(rr, 1, function(x) x - rr[i_cen,]))

# Plot the overall cumulative temperature-mortality association
pdf("plot/figureB_overall_cumulative-temperature_mortality_association.pdf",
    width = 6, height = 5)
plot(x_plot, rep(1, length(x_plot)), type = "n", log = "y",
     xlim = range(x_plot), ylim = c(0.5, 5),
     xlab = "Temperature (°C)", ylab = "Relative risk",
```

```r
     main = "B) Overall cumulative temperature-mortality association",
     axes = FALSE)
axis(1, at = seq(15, 40, by = 5))
axis(2, at = c(0.5, seq(1, 5, by = 1)), labels = c(0.5, seq(1, 5, by = 1)))

# Draw the ensemble of overall accumulated associations
for(i in 1:ncol(rr_plot)){
  lines(x_plot, exp(rr_plot[,i]), lwd = 0.2, col = "lightgrey")
}; rm(i)
abline(h = 1)

# Calculate and draw the summary associations
rr_plot_summary <- apply(rr_plot, 1, quantile, c(0.025, 0.5, 0.975))
lines(x_plot, exp(rr_plot_summary[2,]), lwd = 3)
lines(x_plot, exp(rr_plot_summary[1,]), lwd = 2, lty = 2)
lines(x_plot, exp(rr_plot_summary[3,]), lwd = 2, lty = 2)

dev.off()

# Clean up variables
rm(i_reg, beta_reg, rr, x_plot, i_cen, rr_plot, rr_plot_summary)

#-----------------------------------------------------------------
### C) MAP OF THE RISKS AT PERCENTILE 99
### (SAME AS FIGURE 4C IN THE ORIGINAL SB-DLNM PAPER)
#-----------------------------------------------------------------

# Calculate directly the RR of the overall cumulative temperature-mortality
# associations for all regions
rr <- lapply(1:dlnm_var$n_reg, function(i_reg) {

  # Extract all the samples of the coefficients of the crossbasis
  beta_reg <- cb_res[[i_reg]]

  # The RR in each temperature x is the sum of the product of x transformed
  # through the crossbasis function and the coefficients of the crossbasis
  rr <- apply(beta_reg, 1, function(x) {
    sapply(1:length(x_temp[,i_reg]), function(i) cb[[i_reg]][i,] %*% x)
  })

  rr

})

# Create a function for centring the risk in each region
Center_RR <- function(f.rr, f.cen, f.temp){

  cen <- f.temp[which.min(abs(f.temp - f.cen))]
  rr <- apply(f.rr, 2, function(x) x - x[f.temp == cen])
  rr

}

# Center the relative risk in each region and extract the point estimate at
# percentile 99
rr_plot <- sapply(1:dlnm_var$n_reg, function(i_reg) {
  x_plot <- x_temp[, i_reg]
  cen_plot <- x_plot[percentiles == 0.3]
  rr_plot <- Center_RR(f.rr = rr[[i_reg]],
                       f.cen = cen_plot,
                       f.temp = x_plot)

  # Point estimate as the median of the values at percentile 99
  median(exp(rr_plot[percentiles == 0.99,]))

})

# Set the minimum and maximum RR in the plots
rr_max <- 2
rr_min <- exp(-log(rr_max))

# Force RR are between the maximum and minimum values to avoid NAs
rr_plot[rr_plot < rr_min] <- rr_min
```

```r
rr_plot[rr_plot > rr_max] <- rr_max

# Pallete of colours for the maps
pal <- colorNumeric(palette = rev(
  c("#A90C38", "#C52A40", "#E24848", "#F16B61", "#F89183", "#FEB6A8", "#FEDAD3",
    "#FFFFFF", "#D3E5F2", "#A8CCE5", "#88B4D5", "#6D9CC3", "#5585B1", "#416F9C",
    "#2E5A87")), domain = c(log(rr_min), log(rr_max)), reverse = FALSE)

# Plot the map with the risks
pdf("plot/figureC_map_relative_risks.pdf",
    width = 3, height = 5)

par(mar = c(1, 1, 1, 1), omi = c(0, 0, 0.4, 0))
plot(shapefile_bcn$geometry, col = pal(log(rr_plot)),
     main = "C) Map relative risks")

dev.off()

# Clean up variables
rm(rr, Center_RR, rr_plot, rr_max, rr_min, pal)
```

Figure S1: Overall cumulative temperature-mortality associations for SB-DLNMs using the WinBUGS and R-INLA implementations in the 73 neighbourhoods of Barcelona (2007-2016).

Neighbourhoods are identified with their identification number in the plot titles. Panels labelled with a) (first and third column) show results from the case-crossover design, while panels labelled with b) (second and fourth column) show results from the time-series design. The list of adjacent regions, and the number of deaths in the study period are listed in top of the plots. In each neighbourhood the results for the WinBUGS (purple) and R-INLA implementations (green) are represented. The thick curves represent the points estimates (i.e., median values) of the association between the percentile of the neighbourhood temperature distribution and the relative risk of mortality. To facilitate the comparison, the baseline risk is centred at the 30th percentile of the neighbourhood temperature distribution. The coloured areas represent the 95% credible interval of the estimates. The relative risks (RRs) at the 99th percentile (P99) are provided at the top of the figures, including the point estimates (also marked with dots in the curves) and their corresponding 95% credible intervals.

1a) el Raval: Case−crossover
No. deaths = 929 (Neighbours: 2, 7, 10, 11, 12)
WinBUGS — RR at P99: 1.4 (1.0, 2.3)
R−INLA — RR at P99: 1.4 (1.0, 2.2)
Relative risk
Percentile of the temperature distribution

1b) el Raval: Time−series
No. deaths = 929 (Neighbours: 2, 7, 10, 11, 12)
WinBUGS — RR at P99: 1.4 (1.0, 2.0)
R−INLA — RR at P99: 1.5 (1.0, 2.2)
Relative risk
Percentile of the temperature distribution

2a) el Gòtic: Case−crossover
No. deaths = 365 (Neighbours: 1, 3, 4, 7)
WinBUGS — RR at P99: 1.3 (0.8, 2.2)
R−INLA — RR at P99: 1.3 (0.8, 2.0)
Relative risk
Percentile of the temperature distribution

2b) el Gòtic: Time−series
No. deaths = 365 (Neighbours: 1, 3, 4, 7)
WinBUGS — RR at P99: 1.4 (0.9, 2.1)
R−INLA — RR at P99: 1.5 (0.9, 2.3)
Relative risk
Percentile of the temperature distribution

3a) la Barceloneta: Case−crossover
No. deaths = 456 (Neighbours: 2, 4, 67)
WinBUGS — RR at P99: 1.4 (0.9, 2.2)
R−INLA — RR at P99: 1.4 (0.8, 2.3)
Relative risk
Percentile of the temperature distribution

3b) la Barceloneta: Time−series
No. deaths = 456 (Neighbours: 2, 4, 67)
WinBUGS — RR at P99: 1.3 (0.9, 2.1)
R−INLA — RR at P99: 1.4 (0.9, 2.3)
Relative risk
Percentile of the temperature distribution

4a) Sant Pere, Santa Caterina i la Ribera: Case−crossover
No. deaths = 521 (Neighbours: 2, 3, 5, 7, 66, 67)
WinBUGS — RR at P99: 1.2 (0.8, 1.8)
R−INLA — RR at P99: 1.2 (0.7, 1.7)
Relative risk
Percentile of the temperature distribution

4b) Sant Pere, Santa Caterina i la Ribera: Time−series
No. deaths = 521 (Neighbours: 2, 3, 5, 7, 66, 67)
WinBUGS — RR at P99: 1.3 (0.9, 1.8)
R−INLA — RR at P99: 1.3 (0.8, 2.0)
Relative risk
Percentile of the temperature distribution

5a) el Fort Pienc: Case−crossover
No. deaths = 816 (Neighbours: 4, 6, 7, 66)
WinBUGS — RR at P99: 1.2 (0.8, 1.7)
R−INLA — RR at P99: 1.3 (0.8, 1.9)
Relative risk
Percentile of the temperature distribution

5b) el Fort Pienc: Time−series
No. deaths = 816 (Neighbours: 4, 6, 7, 66)
WinBUGS — RR at P99: 1.3 (0.9, 1.9)
R−INLA — RR at P99: 1.3 (0.9, 2.0)
Relative risk
Percentile of the temperature distribution

6a) la Sagrada Família: Case−crossover
No. deaths = 1444 (Neighbours: 5, 7, 32, 33, 35, 64, 65, 66)
WinBUGS — RR at P99: 1.2 (0.9, 1.6)
R−INLA — RR at P99: 1.2 (0.9, 1.8)
Relative risk
Percentile of the temperature distribution

6b) la Sagrada Família: Time−series
No. deaths = 1444 (Neighbours: 5, 7, 32, 33, 35, 64, 65, 66)
WinBUGS — RR at P99: 1.3 (1.0, 1.8)
R−INLA — RR at P99: 1.4 (1.0, 1.9)
Relative risk
Percentile of the temperature distribution

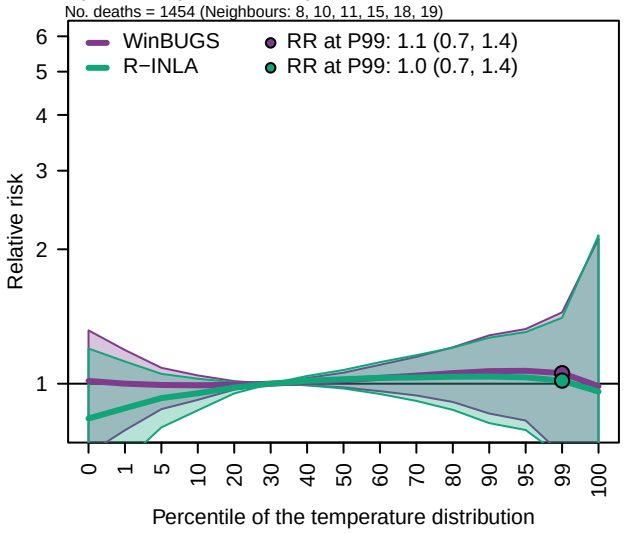
7a) la Dreta de l'Eixample: Case−crossover
No. deaths = 1446 (Neighbours: 1, 2, 4, 5, 6, 8, 10, 26, 31, 32)
WinBUGS — RR at P99: 1.2 (0.9, 1.6)
R−INLA — RR at P99: 1.2 (0.8, 1.6)
Relative risk
Percentile of the temperature distribution

7b) la Dreta de l'Eixample: Time−series
No. deaths = 1446 (Neighbours: 1, 2, 4, 5, 6, 8, 10, 26, 31, 32)
WinBUGS — RR at P99: 1.3 (1.0, 1.6)
R−INLA — RR at P99: 1.2 (0.9, 1.7)
Relative risk
Percentile of the temperature distribution

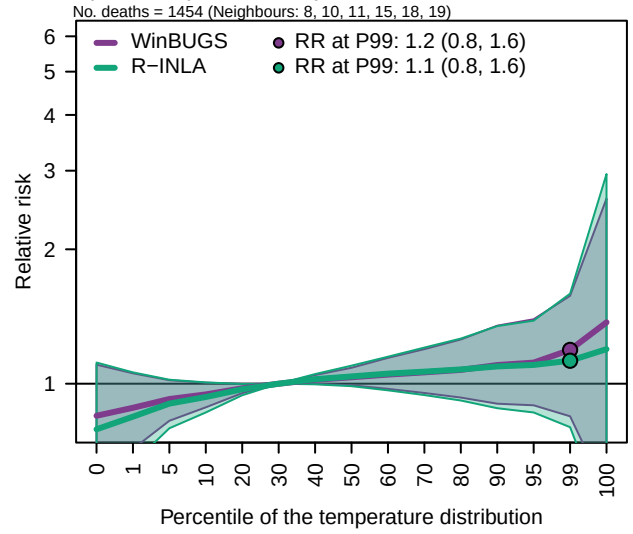
8a) l'Antiga Esquerra de l'Eixample: Case−crossover
No. deaths = 1206 (Neighbours: 7, 9, 10, 19, 26)
WinBUGS — RR at P99: 1.3 (0.9, 1.8)
R−INLA — RR at P99: 1.3 (0.9, 1.9)
Relative risk
Percentile of the temperature distribution

8b) l'Antiga Esquerra de l'Eixample: Time−series
No. deaths = 1206 (Neighbours: 7, 9, 10, 19, 26)
WinBUGS — RR at P99: 1.3 (0.9, 1.9)
R−INLA — RR at P99: 1.4 (0.9, 2.0)
Relative risk
Percentile of the temperature distribution

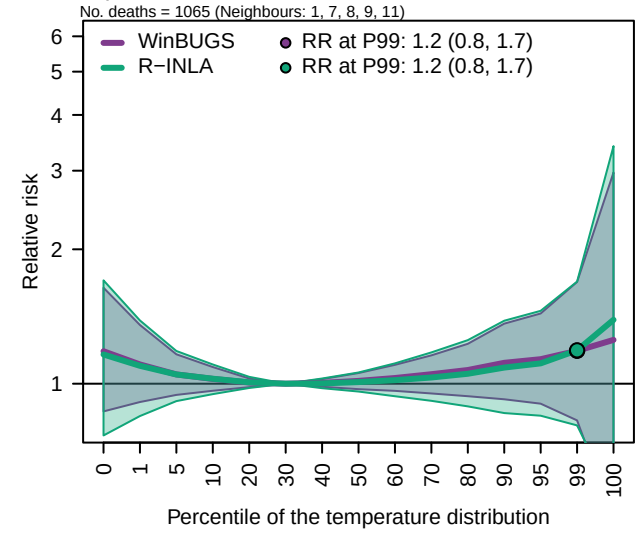
9a) la Nova Esquerra de l'Eixample: Case−crossover
No. deaths = 1454 (Neighbours: 8, 10, 11, 15, 18, 19)



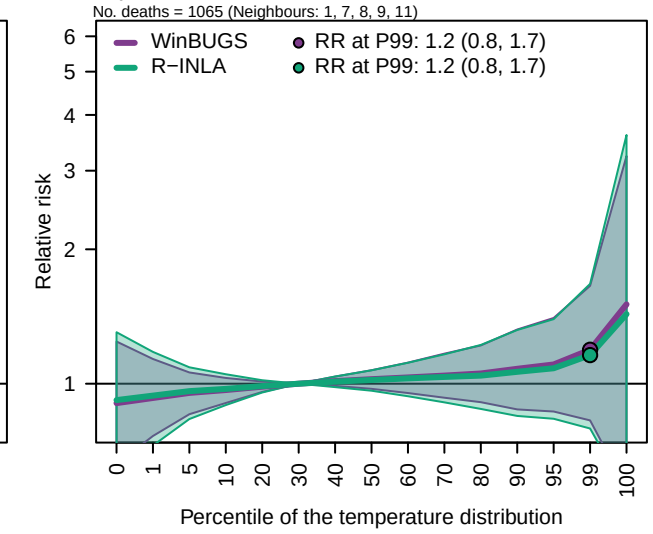
9b) la Nova Esquerra de l'Eixample: Time−series
No. deaths = 1454 (Neighbours: 8, 10, 11, 15, 18, 19)



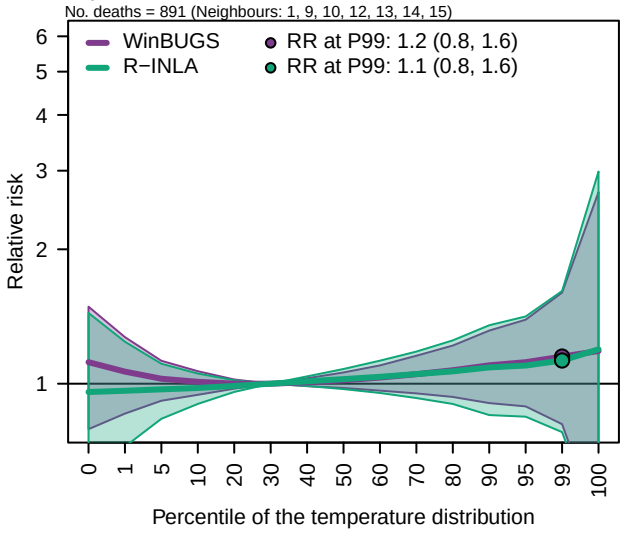
10a) Sant Antoni: Case−crossover
No. deaths = 1065 (Neighbours: 1, 7, 8, 9, 11)



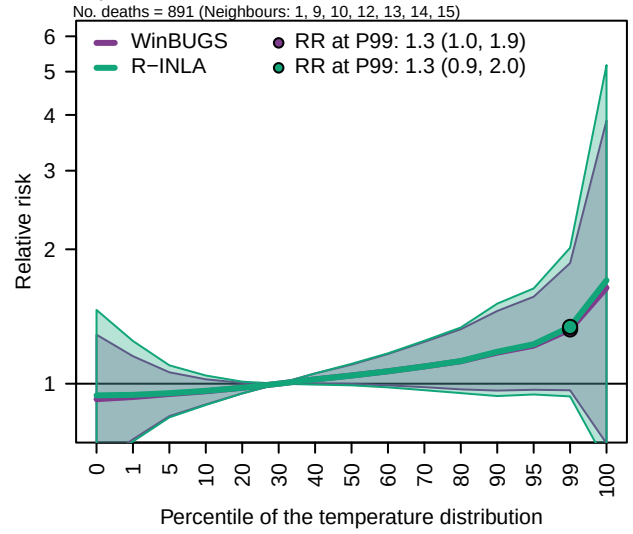
10b) Sant Antoni: Time−series
No. deaths = 1065 (Neighbours: 1, 7, 8, 9, 11)



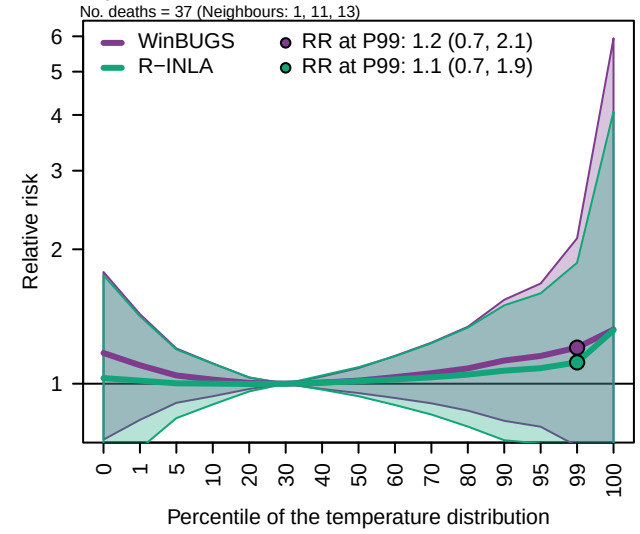
11a) el Poble Sec: Case−crossover
No. deaths = 891 (Neighbours: 1, 9, 10, 12, 13, 14, 15)



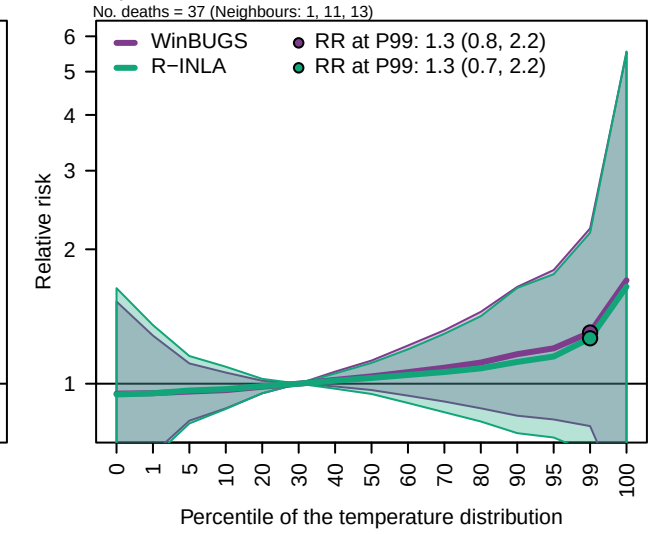
11b) el Poble Sec: Time−series
No. deaths = 891 (Neighbours: 1, 9, 10, 12, 13, 14, 15)



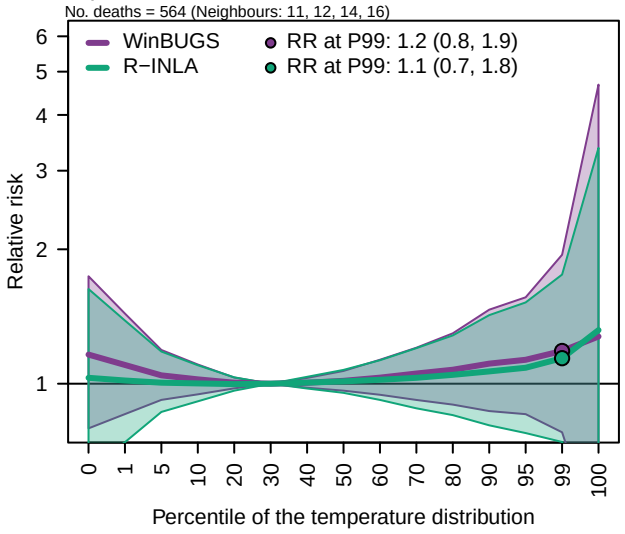
12a) la Marina del Prat Vermell: Case−crossover
No. deaths = 37 (Neighbours: 1, 11, 13)



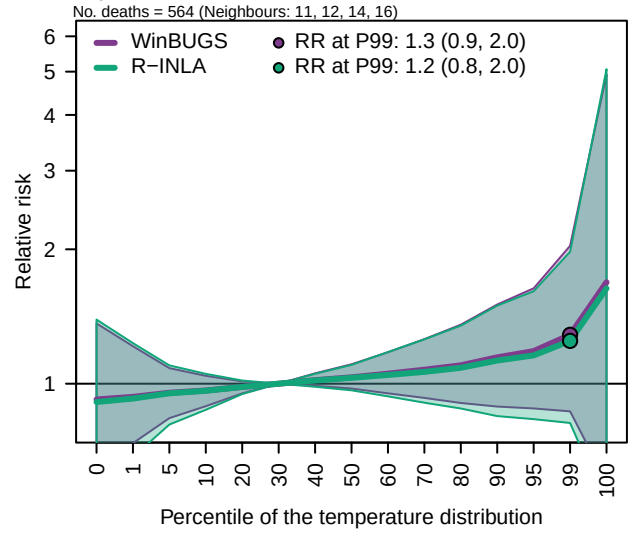
12b) la Marina del Prat Vermell: Time−series
No. deaths = 37 (Neighbours: 1, 11, 13)



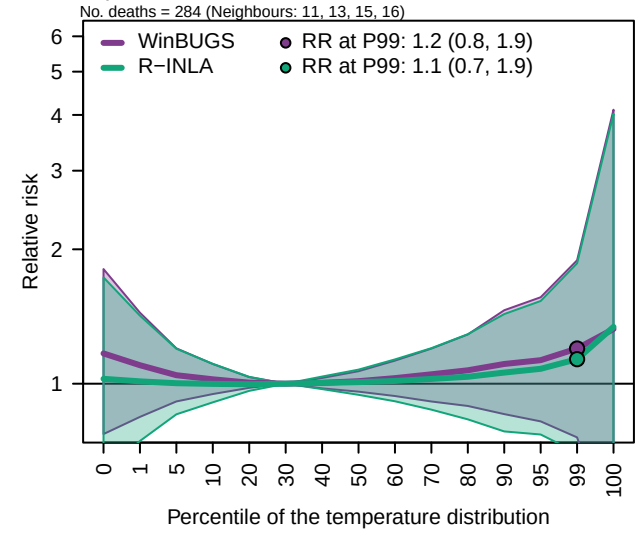
13a) la Marina de Port: Case−crossover
No. deaths = 564 (Neighbours: 11, 12, 14, 16)



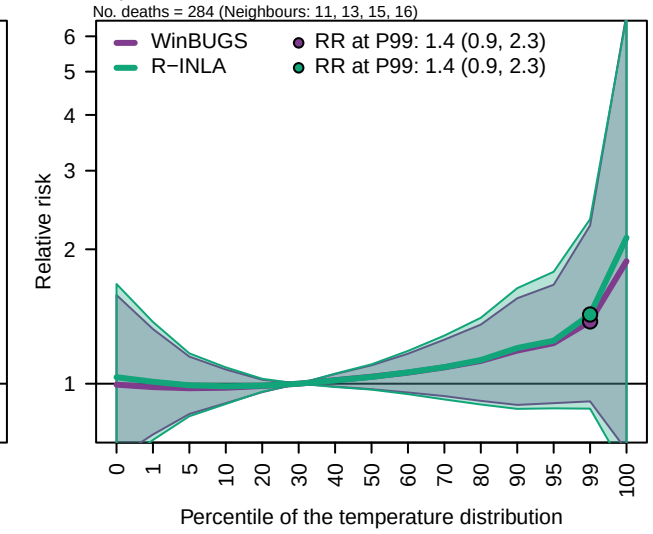
13b) la Marina de Port: Time−series
No. deaths = 564 (Neighbours: 11, 12, 14, 16)



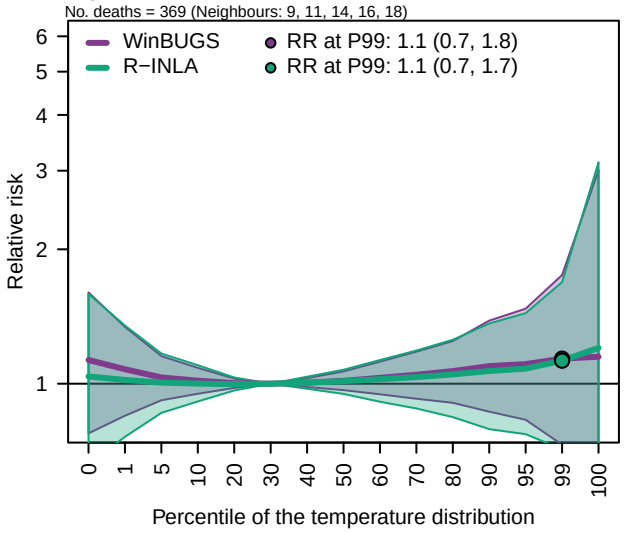
14a) la Font de la Guatlla: Case−crossover
No. deaths = 284 (Neighbours: 11, 13, 15, 16)



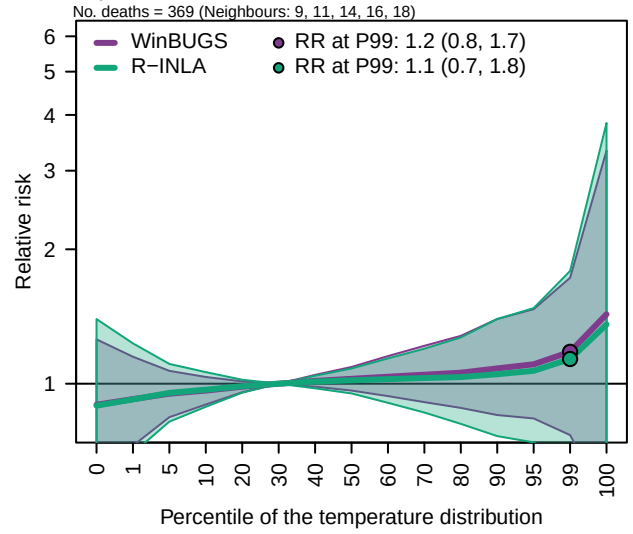
14b) la Font de la Guatlla: Time−series
No. deaths = 284 (Neighbours: 11, 13, 15, 16)



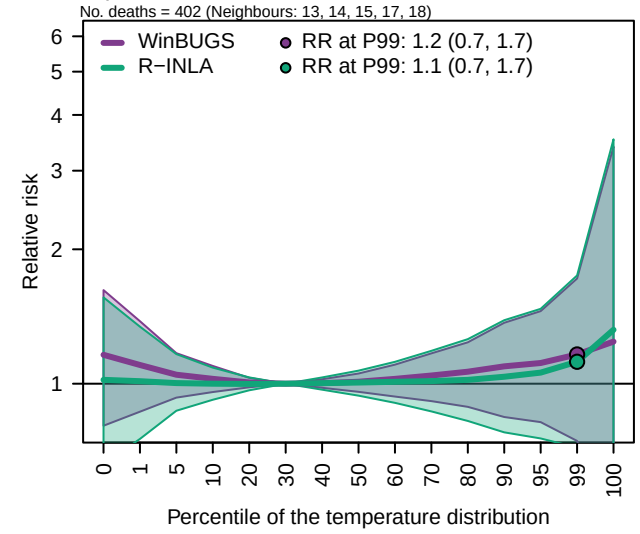
15a) Hostafrancs: Case−crossover
No. deaths = 369 (Neighbours: 9, 11, 14, 16, 18)



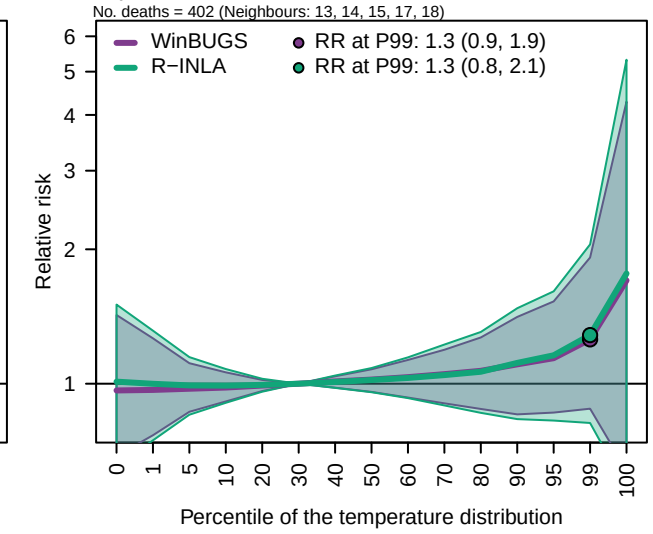
15b) Hostafrancs: Time−series
No. deaths = 369 (Neighbours: 9, 11, 14, 16, 18)

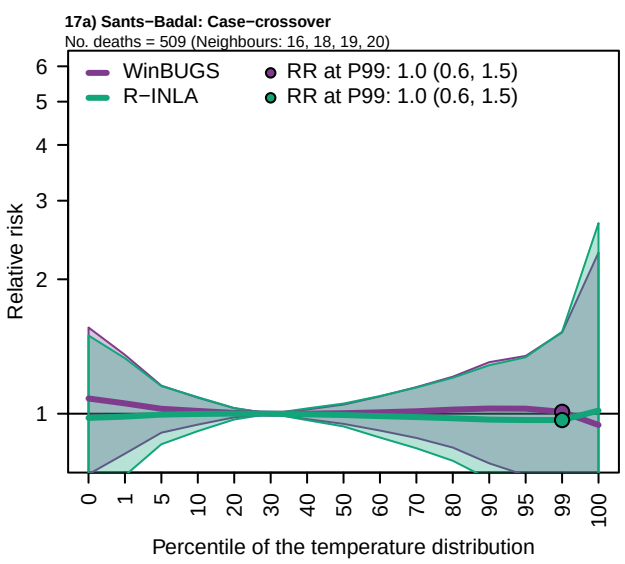


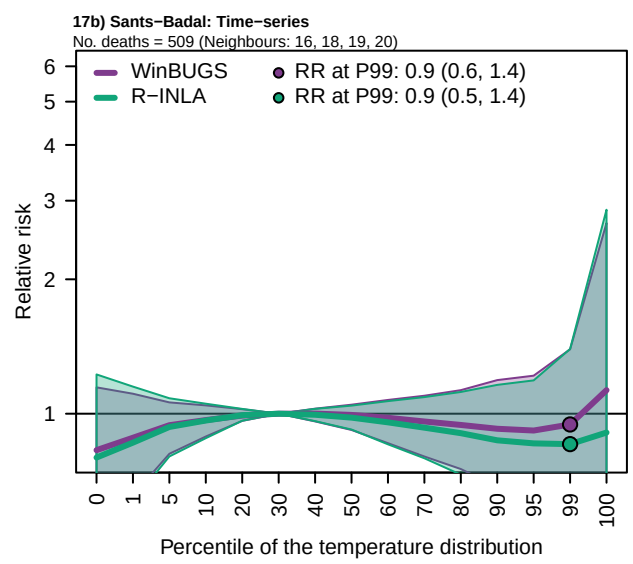
16a) la Bordeta: Case−crossover
No. deaths = 402 (Neighbours: 13, 14, 15, 17, 18)

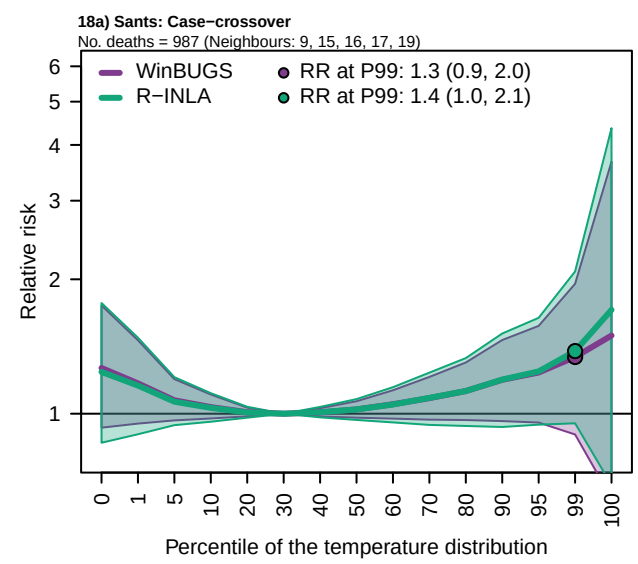


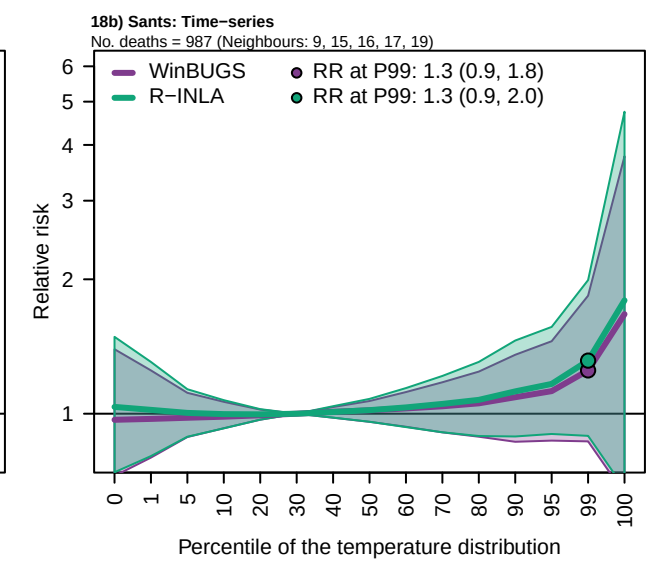
16b) la Bordeta: Time−series
No. deaths = 402 (Neighbours: 13, 14, 15, 17, 18)

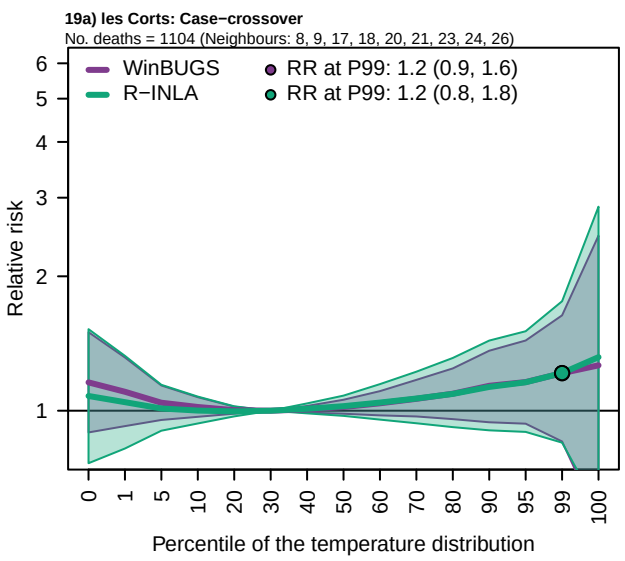


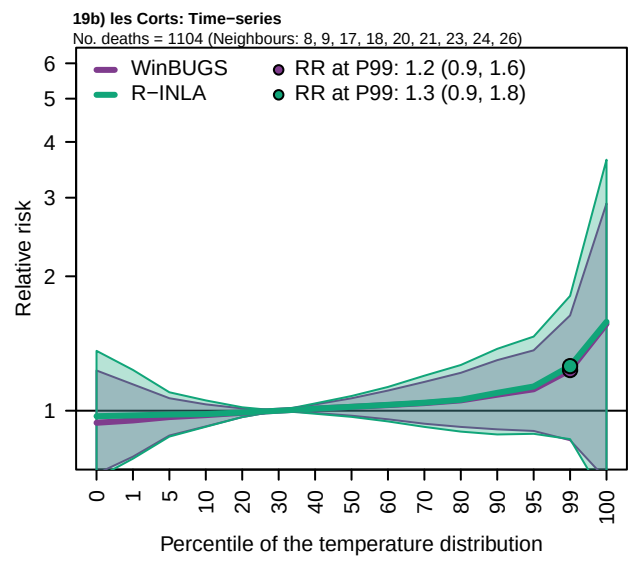

17a) Sants−Badal: Case−crossover
No. deaths = 509 (Neighbours: 16, 18, 19, 20)
WinBUGS
R−INLA
RR at P99: 1.0 (0.6, 1.5)
RR at P99: 1.0 (0.6, 1.5)
Relative risk
Percentile of the temperature distribution

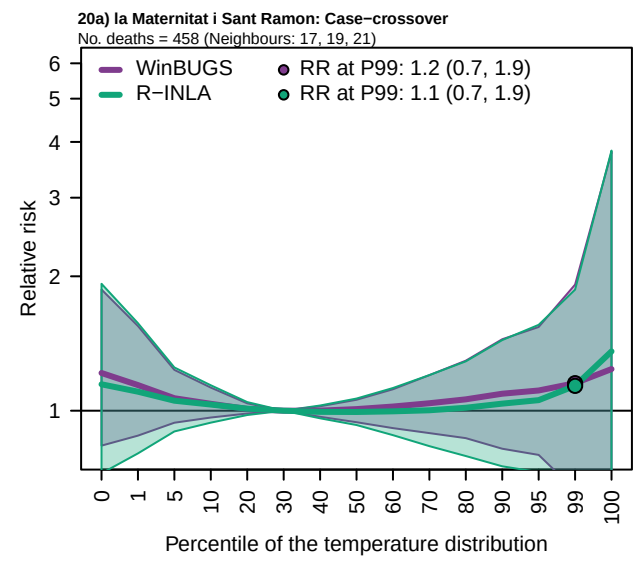

17b) Sants−Badal: Time−series
No. deaths = 509 (Neighbours: 16, 18, 19, 20)
WinBUGS
R−INLA
RR at P99: 0.9 (0.6, 1.4)
RR at P99: 0.9 (0.5, 1.4)
Relative risk
Percentile of the temperature distribution

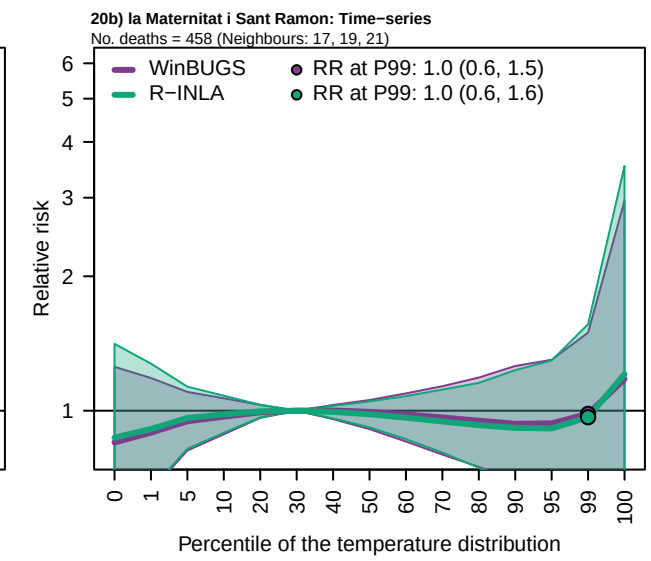

18a) Sants: Case−crossover
No. deaths = 987 (Neighbours: 9, 15, 16, 17, 19)
WinBUGS
R−INLA
RR at P99: 1.3 (0.9, 2.0)
RR at P99: 1.4 (1.0, 2.1)
Relative risk
Percentile of the temperature distribution

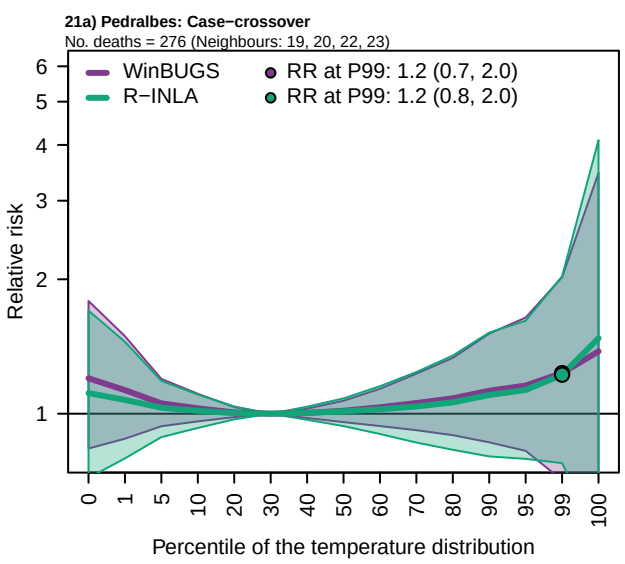

18b) Sants: Time−series
No. deaths = 987 (Neighbours: 9, 15, 16, 17, 19)
WinBUGS
R−INLA
RR at P99: 1.3 (0.9, 1.8)
RR at P99: 1.3 (0.9, 2.0)
Relative risk
Percentile of the temperature distribution

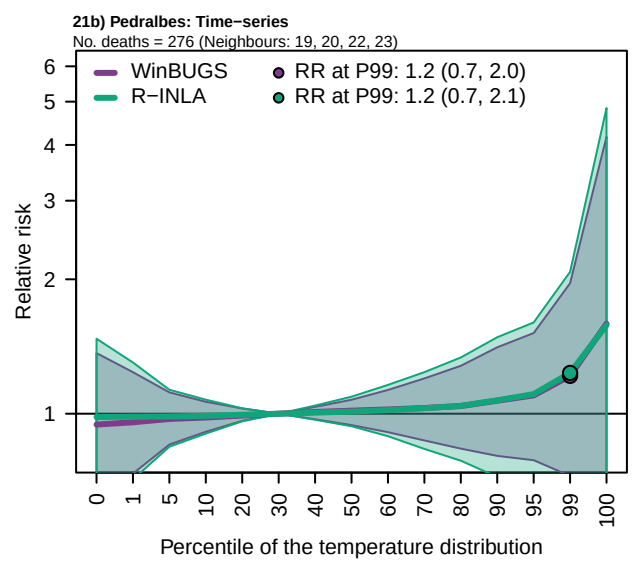

19a) les Corts: Case−crossover
No. deaths = 1104 (Neighbours: 8, 9, 17, 18, 20, 21, 23, 24, 26)
WinBUGS
R−INLA
RR at P99: 1.2 (0.9, 1.6)
RR at P99: 1.2 (0.8, 1.8)
Relative risk
Percentile of the temperature distribution

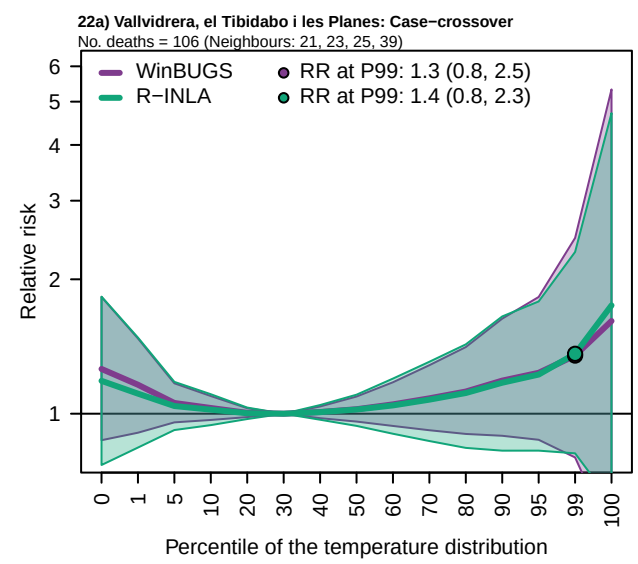

19b) les Corts: Time−series
No. deaths = 1104 (Neighbours: 8, 9, 17, 18, 20, 21, 23, 24, 26)
WinBUGS
R−INLA
RR at P99: 1.2 (0.9, 1.6)
RR at P99: 1.3 (0.9, 1.8)
Relative risk
Percentile of the temperature distribution

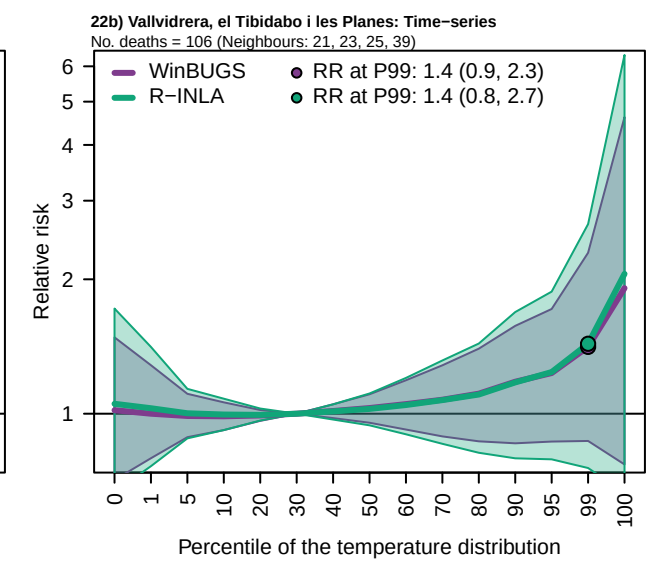

20a) la Maternitat i Sant Ramon: Case−crossover
No. deaths = 458 (Neighbours: 17, 19, 21)
WinBUGS
R−INLA
RR at P99: 1.2 (0.7, 1.9)
RR at P99: 1.1 (0.7, 1.9)
Relative risk
Percentile of the temperature distribution

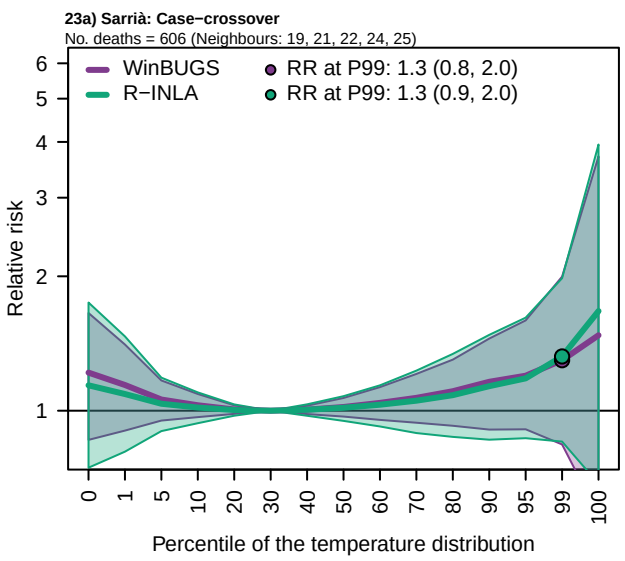

20b) la Maternitat i Sant Ramon: Time−series
No. deaths = 458 (Neighbours: 17, 19, 21)
WinBUGS
R−INLA
RR at P99: 1.0 (0.6, 1.5)
RR at P99: 1.0 (0.6, 1.6)
Relative risk
Percentile of the temperature distribution

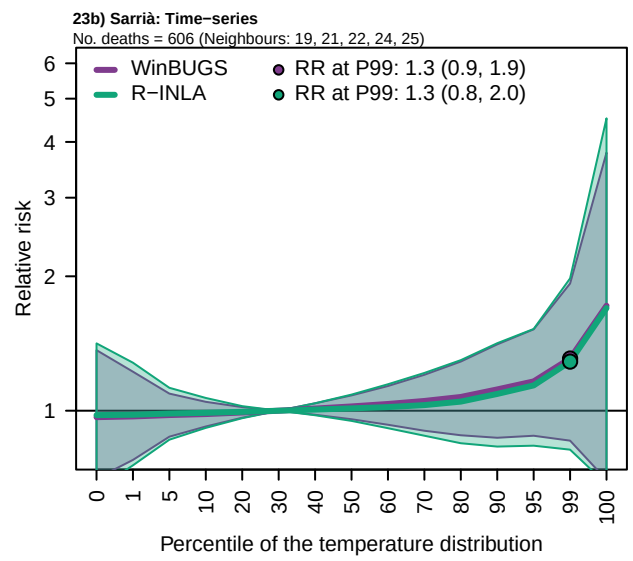

21a) Pedralbes: Case−crossover
No. deaths = 276 (Neighbours: 19, 20, 22, 23)
WinBUGS
R−INLA
RR at P99: 1.2 (0.7, 2.0)
RR at P99: 1.2 (0.8, 2.0)
Relative risk
Percentile of the temperature distribution

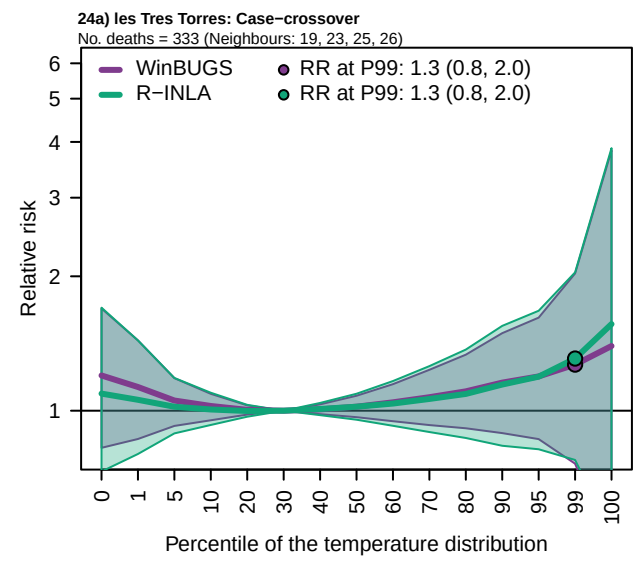

21b) Pedralbes: Time−series
No. deaths = 276 (Neighbours: 19, 20, 22, 23)
WinBUGS
R−INLA
RR at P99: 1.2 (0.7, 2.0)
RR at P99: 1.2 (0.7, 2.1)
Relative risk
Percentile of the temperature distribution

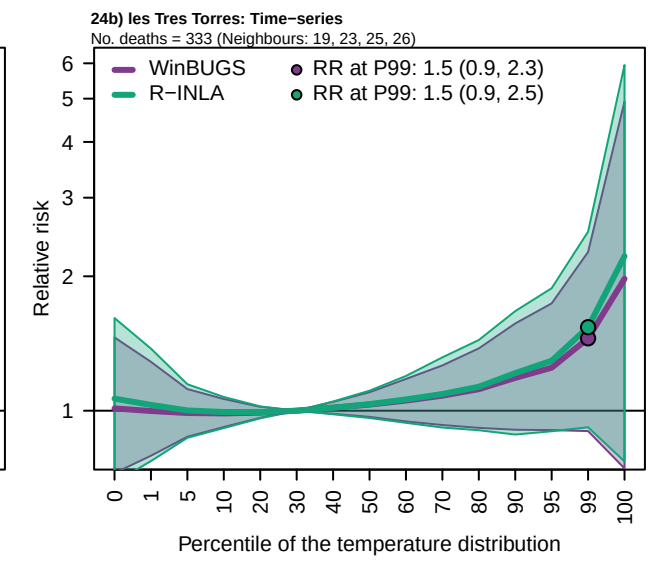

22a) Vallvidrera, el Tibidabo i les Planes: Case−crossover
No. deaths = 106 (Neighbours: 21, 23, 25, 39)
WinBUGS
R−INLA
RR at P99: 1.3 (0.8, 2.5)
RR at P99: 1.4 (0.8, 2.3)
Relative risk
Percentile of the temperature distribution


22b) Vallvidrera, el Tibidabo i les Planes: Time−series
No. deaths = 106 (Neighbours: 21, 23, 25, 39)
WinBUGS
R−INLA
RR at P99: 1.4 (0.9, 2.3)
RR at P99: 1.4 (0.8, 2.7)
Relative risk
Percentile of the temperature distribution


23a) Sarrià: Case−crossover
No. deaths = 606 (Neighbours: 19, 21, 22, 24, 25)
WinBUGS
R−INLA
RR at P99: 1.3 (0.8, 2.0)
RR at P99: 1.3 (0.9, 2.0)
Relative risk
Percentile of the temperature distribution


23b) Sarrià: Time−series
No. deaths = 606 (Neighbours: 19, 21, 22, 24, 25)
WinBUGS
R−INLA
RR at P99: 1.3 (0.9, 1.9)
RR at P99: 1.3 (0.8, 2.0)
Relative risk
Percentile of the temperature distribution


24a) les Tres Torres: Case−crossover
No. deaths = 333 (Neighbours: 19, 23, 25, 26)
WinBUGS
R−INLA
RR at P99: 1.3 (0.8, 2.0)
RR at P99: 1.3 (0.8, 2.0)
Relative risk
Percentile of the temperature distribution


24b) les Tres Torres: Time−series
No. deaths = 333 (Neighbours: 19, 23, 25, 26)
WinBUGS
R−INLA
RR at P99: 1.5 (0.9, 2.3)
RR at P99: 1.5 (0.9, 2.5)
Relative risk
Percentile of the temperature distribution

25a) Sant Gervasi−Bonanova: Case−crossover
No. deaths = 707 (Neighbours: 22, 23, 24, 26, 27, 28, 39)
WinBUGS — RR at P99: 1.3 (0.9, 2.1)
R−INLA — RR at P99: 1.3 (0.8, 1.9)
Relative risk
Percentile of the temperature distribution

25b) Sant Gervasi−Bonanova: Time−series
No. deaths = 707 (Neighbours: 22, 23, 24, 26, 27, 28, 39)
WinBUGS — RR at P99: 1.6 (1.1, 2.3)
R−INLA — RR at P99: 1.6 (1.1, 2.5)
Relative risk
Percentile of the temperature distribution

26a) Sant Gervasi−Galvany: Case−crossover
No. deaths = 1165 (Neighbours: 7, 8, 19, 24, 25, 27, 31)
WinBUGS — RR at P99: 1.2 (0.8, 1.7)
R−INLA — RR at P99: 1.2 (0.8, 1.7)
Relative risk
Percentile of the temperature distribution

26b) Sant Gervasi−Galvany: Time−series
No. deaths = 1165 (Neighbours: 7, 8, 19, 24, 25, 27, 31)
WinBUGS — RR at P99: 1.3 (1.0, 1.8)
R−INLA — RR at P99: 1.3 (0.9, 1.9)
Relative risk
Percentile of the temperature distribution

27a) el Putget i Farró: Case−crossover
No. deaths = 643 (Neighbours: 25, 26, 28, 31)
WinBUGS — RR at P99: 1.8 (1.1, 3.2)
R−INLA — RR at P99: 1.7 (1.1, 2.9)
Relative risk
Percentile of the temperature distribution

27b) el Putget i Farró: Time−series
No. deaths = 643 (Neighbours: 25, 26, 28, 31)
WinBUGS — RR at P99: 2.1 (1.4, 3.7)
R−INLA — RR at P99: 2.5 (1.5, 4.1)
Relative risk
Percentile of the temperature distribution

28a) Vallcarca i els Penitents: Case−crossover
No. deaths = 385 (Neighbours: 25, 27, 29, 30, 31, 38, 39)
WinBUGS — RR at P99: 1.5 (1.0, 2.5)
R−INLA — RR at P99: 1.6 (1.0, 2.5)
Relative risk
Percentile of the temperature distribution

28b) Vallcarca i els Penitents: Time−series
No. deaths = 385 (Neighbours: 25, 27, 29, 30, 31, 38, 39)
WinBUGS — RR at P99: 1.6 (1.1, 2.4)
R−INLA — RR at P99: 1.5 (0.9, 2.6)
Relative risk
Percentile of the temperature distribution

29a) el Coll: Case−crossover
No. deaths = 145 (Neighbours: 28, 30, 37, 38)
WinBUGS — RR at P99: 1.4 (0.8, 2.5)
R−INLA — RR at P99: 1.4 (0.8, 2.3)
Relative risk
Percentile of the temperature distribution

29b) el Coll: Time−series
No. deaths = 145 (Neighbours: 28, 30, 37, 38)
WinBUGS — RR at P99: 1.5 (0.8, 2.4)
R−INLA — RR at P99: 1.5 (0.8, 2.7)
Relative risk
Percentile of the temperature distribution

30a) la Salut: Case−crossover
No. deaths = 390 (Neighbours: 28, 29, 31, 32, 33, 34, 37)
WinBUGS — RR at P99: 1.5 (1.0, 2.7)
R−INLA — RR at P99: 1.6 (1.0, 2.8)
Relative risk
Percentile of the temperature distribution

30b) la Salut: Time−series
No. deaths = 390 (Neighbours: 28, 29, 31, 32, 33, 34, 37)
WinBUGS — RR at P99: 1.6 (1.0, 2.5)
R−INLA — RR at P99: 1.8 (1.1, 2.9)
Relative risk
Percentile of the temperature distribution

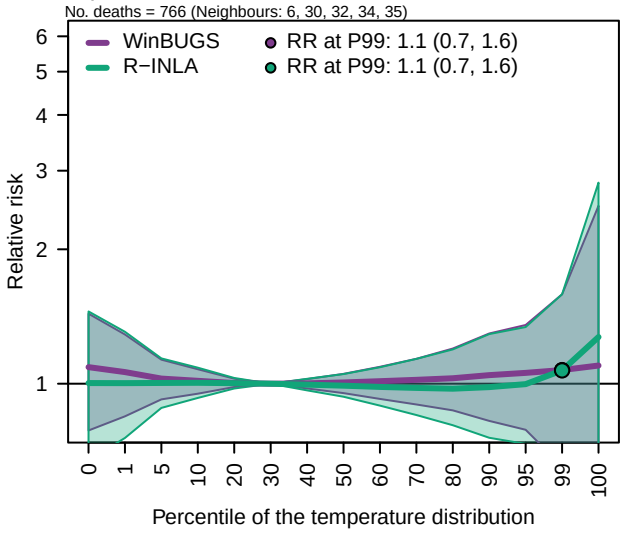
31a) Vila de Gràcia: Case−crossover
No. deaths = 1445 (Neighbours: 7, 26, 27, 28, 30, 32)
WinBUGS — RR at P99: 1.6 (1.2, 2.3)
R−INLA — RR at P99: 1.6 (1.1, 2.4)
Relative risk
Percentile of the temperature distribution

31b) Vila de Gràcia: Time−series
No. deaths = 1445 (Neighbours: 7, 26, 27, 28, 30, 32)
WinBUGS — RR at P99: 1.5 (1.2, 2.3)
R−INLA — RR at P99: 1.6 (1.1, 2.3)
Relative risk
Percentile of the temperature distribution

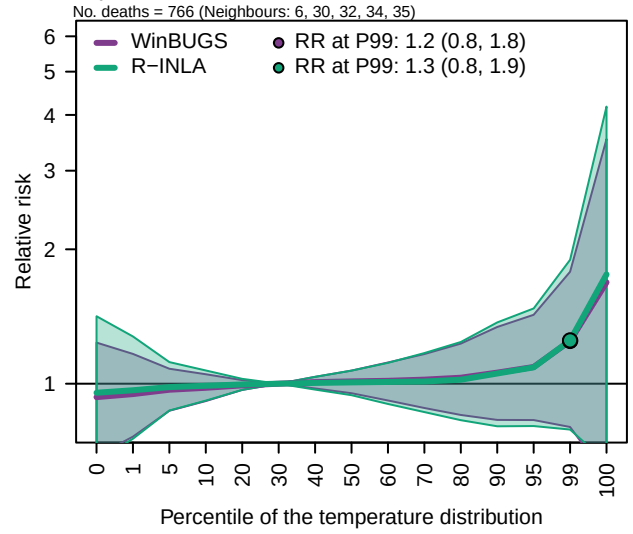
32a) el Camp d'en Grassot i Gràcia Nova: Case−crossover
No. deaths = 892 (Neighbours: 6, 7, 30, 31, 33)
WinBUGS — RR at P99: 1.1 (0.7, 1.6)
R−INLA — RR at P99: 1.1 (0.7, 1.6)
Relative risk
Percentile of the temperature distribution

32b) el Camp d'en Grassot i Gràcia Nova: Time−series
No. deaths = 892 (Neighbours: 6, 7, 30, 31, 33)
WinBUGS — RR at P99: 1.3 (0.9, 1.9)
R−INLA — RR at P99: 1.3 (0.9, 1.9)
Relative risk
Percentile of the temperature distribution

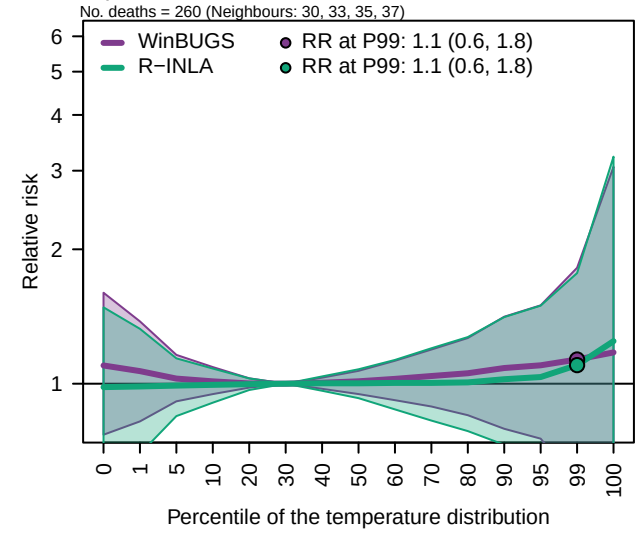
33a) el Baix Guinardó: Case−crossover
No. deaths = 766 (Neighbours: 6, 30, 32, 34, 35)
WinBUGS — RR at P99: 1.1 (0.7, 1.6)
R−INLA — RR at P99: 1.1 (0.7, 1.6)



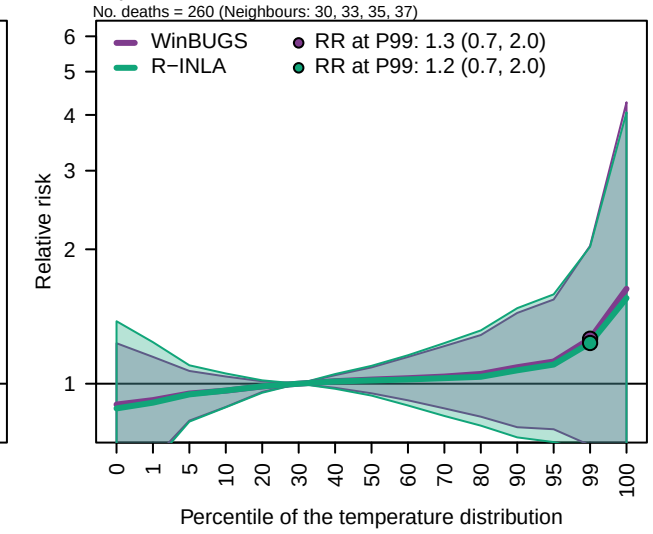
33b) el Baix Guinardó: Time−series
No. deaths = 766 (Neighbours: 6, 30, 32, 34, 35)
WinBUGS — RR at P99: 1.2 (0.8, 1.8)
R−INLA — RR at P99: 1.3 (0.8, 1.9)



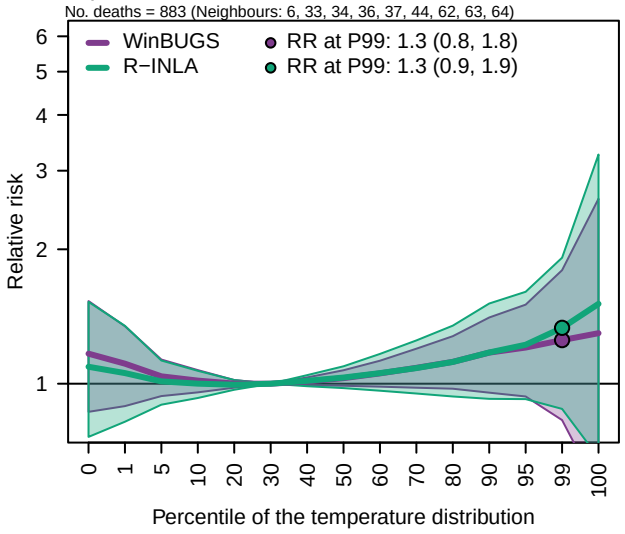
34a) Can Baró: Case−crossover
No. deaths = 260 (Neighbours: 30, 33, 35, 37)
WinBUGS — RR at P99: 1.1 (0.6, 1.8)
R−INLA — RR at P99: 1.1 (0.6, 1.8)



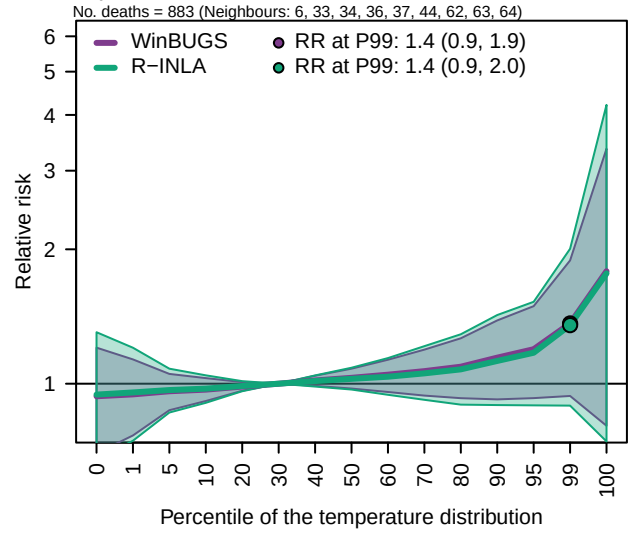
34b) Can Baró: Time−series
No. deaths = 260 (Neighbours: 30, 33, 35, 37)
WinBUGS — RR at P99: 1.3 (0.7, 2.0)
R−INLA — RR at P99: 1.2 (0.7, 2.0)



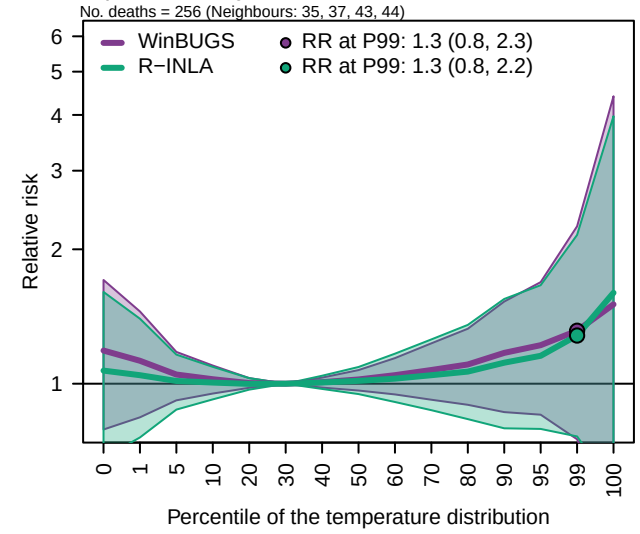
35a) el Guinardó: Case−crossover
No. deaths = 883 (Neighbours: 6, 33, 34, 36, 37, 44, 62, 63, 64)
WinBUGS — RR at P99: 1.3 (0.8, 1.8)
R−INLA — RR at P99: 1.3 (0.9, 1.9)



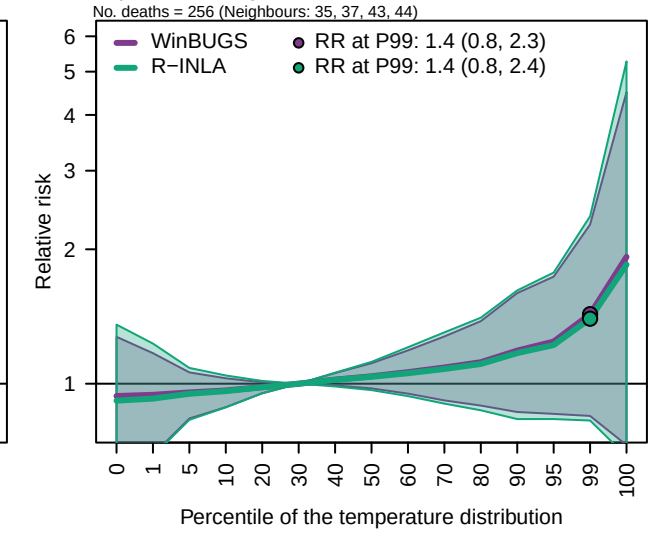
35b) el Guinardó: Time−series
No. deaths = 883 (Neighbours: 6, 33, 34, 36, 37, 44, 62, 63, 64)
WinBUGS — RR at P99: 1.4 (0.9, 1.9)
R−INLA — RR at P99: 1.4 (0.9, 2.0)



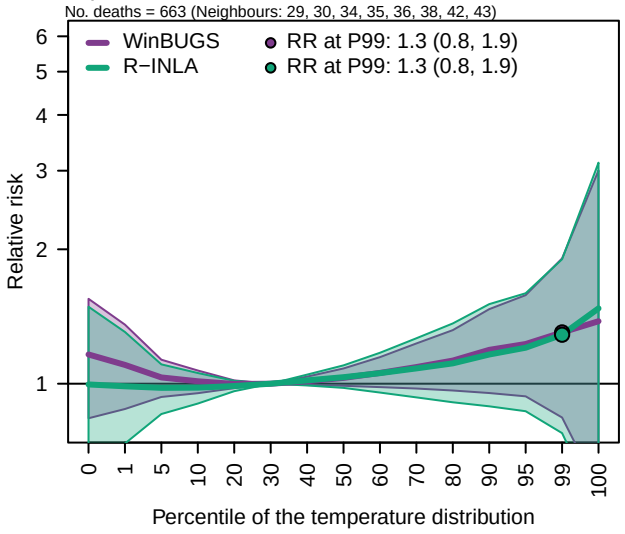
36a) la Font d'en Fargues: Case−crossover
No. deaths = 256 (Neighbours: 35, 37, 43, 44)
WinBUGS — RR at P99: 1.3 (0.8, 2.3)
R−INLA — RR at P99: 1.3 (0.8, 2.2)



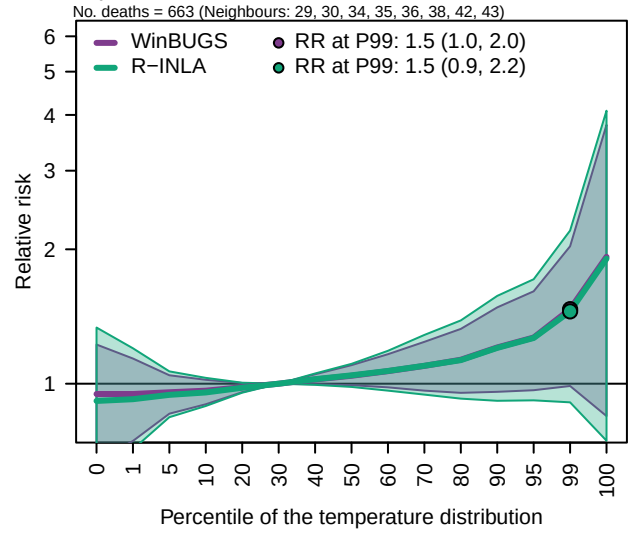
36b) la Font d'en Fargues: Time−series
No. deaths = 256 (Neighbours: 35, 37, 43, 44)
WinBUGS — RR at P99: 1.4 (0.8, 2.3)
R−INLA — RR at P99: 1.4 (0.8, 2.4)



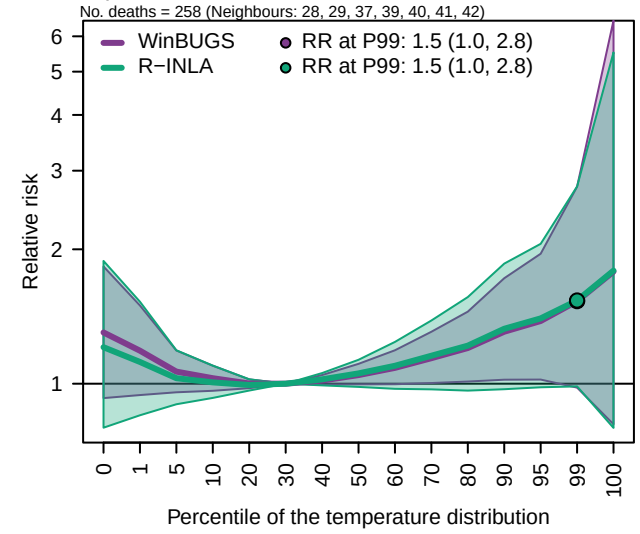
37a) el Carmel: Case−crossover
No. deaths = 663 (Neighbours: 29, 30, 34, 35, 36, 38, 42, 43)
WinBUGS — RR at P99: 1.3 (0.8, 1.9)
R−INLA — RR at P99: 1.3 (0.8, 1.9)



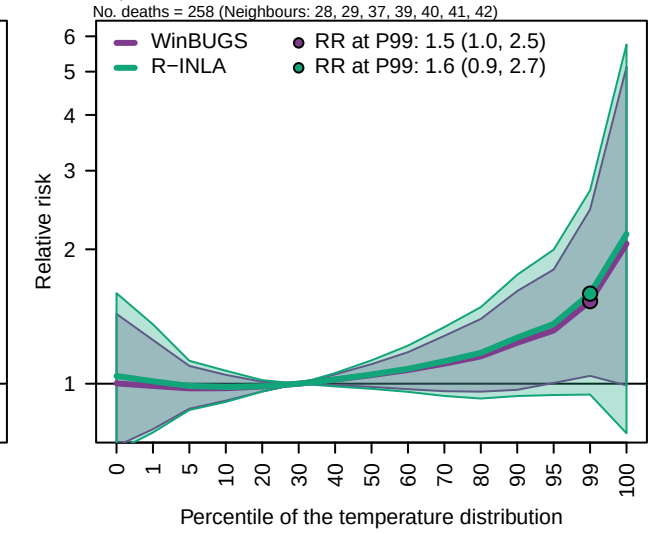
37b) el Carmel: Time−series
No. deaths = 663 (Neighbours: 29, 30, 34, 35, 36, 38, 42, 43)
WinBUGS — RR at P99: 1.5 (1.0, 2.0)
R−INLA — RR at P99: 1.5 (0.9, 2.2)



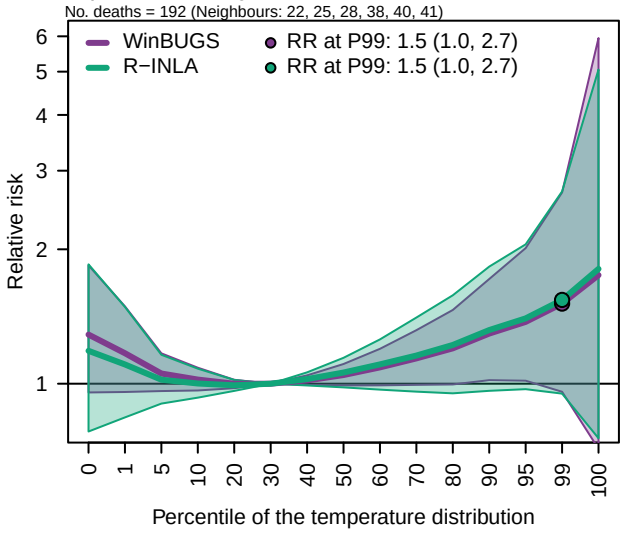
38a) la Teixonera: Case−crossover
No. deaths = 258 (Neighbours: 28, 29, 37, 39, 40, 41, 42)
WinBUGS — RR at P99: 1.5 (1.0, 2.8)
R−INLA — RR at P99: 1.5 (1.0, 2.8)



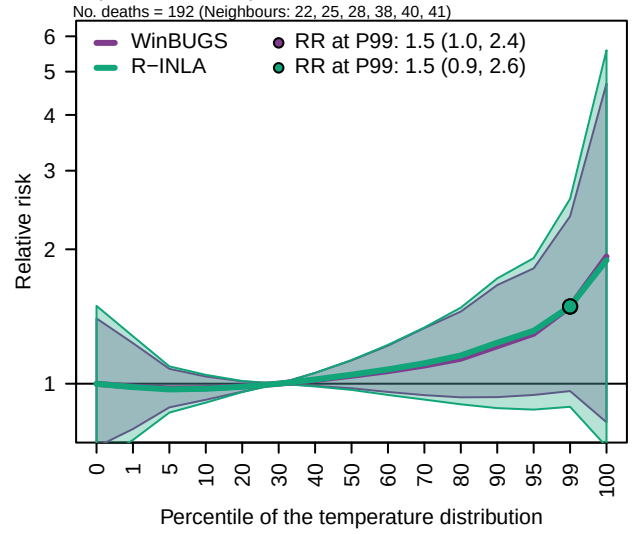
38b) la Teixonera: Time−series
No. deaths = 258 (Neighbours: 28, 29, 37, 39, 40, 41, 42)
WinBUGS — RR at P99: 1.5 (1.0, 2.5)
R−INLA — RR at P99: 1.6 (0.9, 2.7)



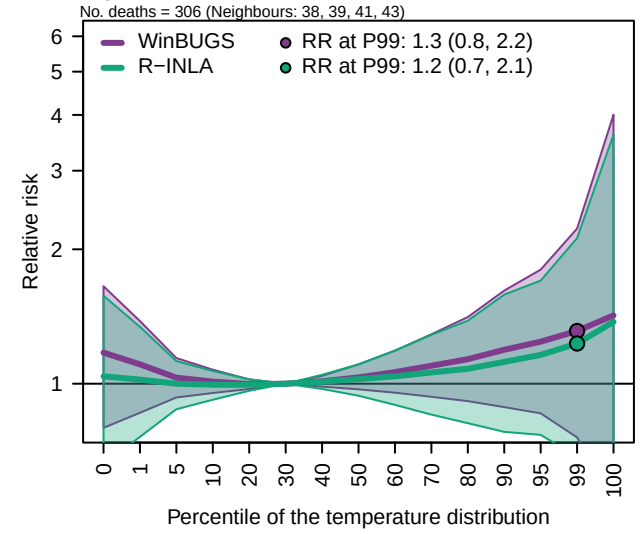
39a) Sant Genís dels Agudells: Case−crossover
No. deaths = 192 (Neighbours: 22, 25, 28, 38, 40, 41)
WinBUGS — RR at P99: 1.5 (1.0, 2.7)
R−INLA — RR at P99: 1.5 (1.0, 2.7)



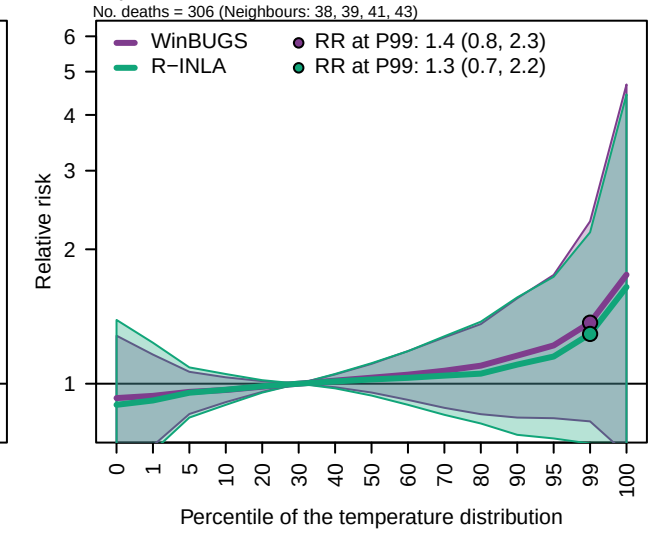
39b) Sant Genís dels Agudells: Time−series
No. deaths = 192 (Neighbours: 22, 25, 28, 38, 40, 41)
WinBUGS — RR at P99: 1.5 (1.0, 2.4)
R−INLA — RR at P99: 1.5 (0.9, 2.6)



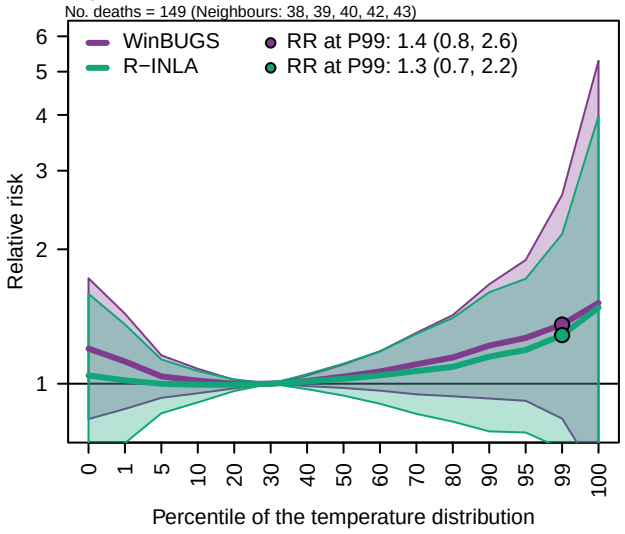
40a) Montbau: Case−crossover
No. deaths = 306 (Neighbours: 38, 39, 41, 43)
WinBUGS — RR at P99: 1.3 (0.8, 2.2)
R−INLA — RR at P99: 1.2 (0.7, 2.1)



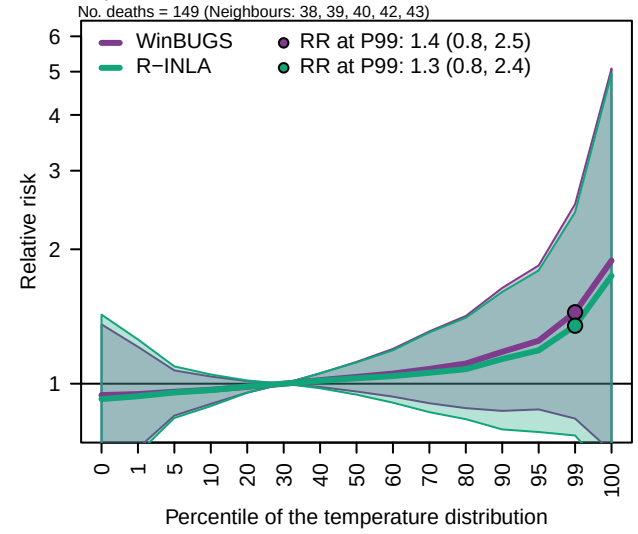
40b) Montbau: Time−series
No. deaths = 306 (Neighbours: 38, 39, 41, 43)
WinBUGS — RR at P99: 1.4 (0.8, 2.3)
R−INLA — RR at P99: 1.3 (0.7, 2.2)



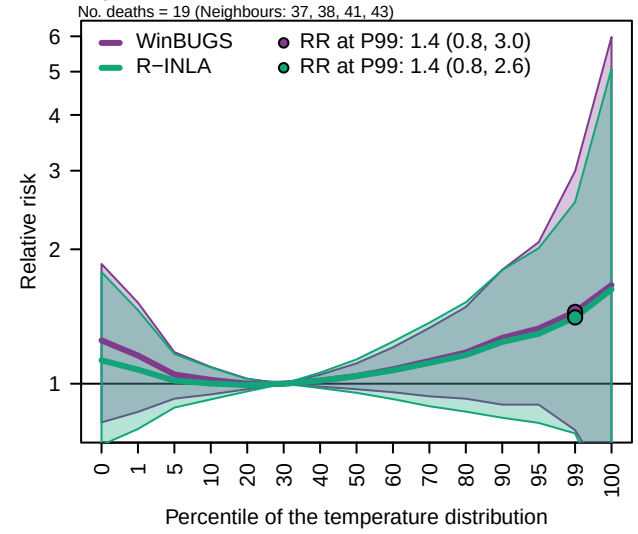
41a) la Vall d'Hebron: Case−crossover
No. deaths = 149 (Neighbours: 38, 39, 40, 42, 43)



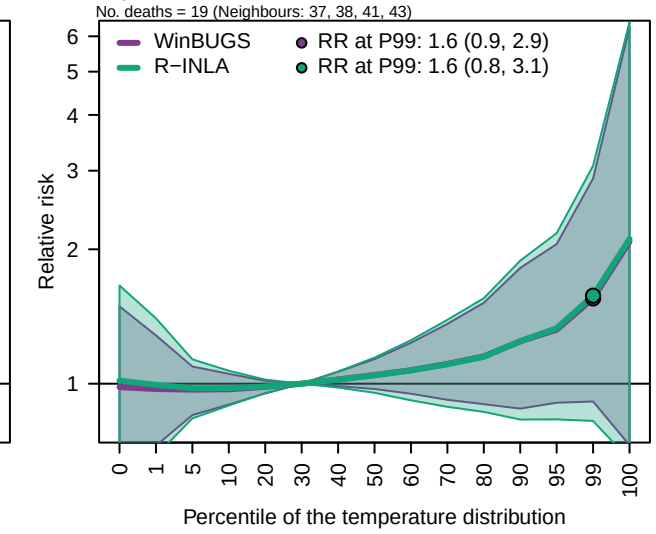
41b) la Vall d'Hebron: Time−series
No. deaths = 149 (Neighbours: 38, 39, 40, 42, 43)



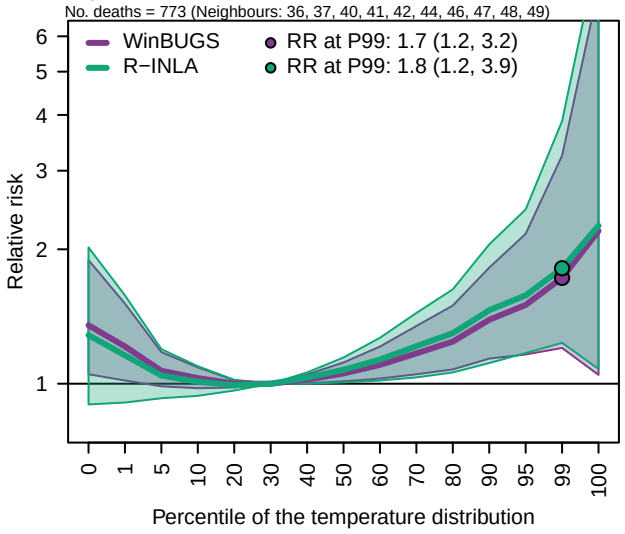
42a) la Clota: Case−crossover
No. deaths = 19 (Neighbours: 37, 38, 41, 43)



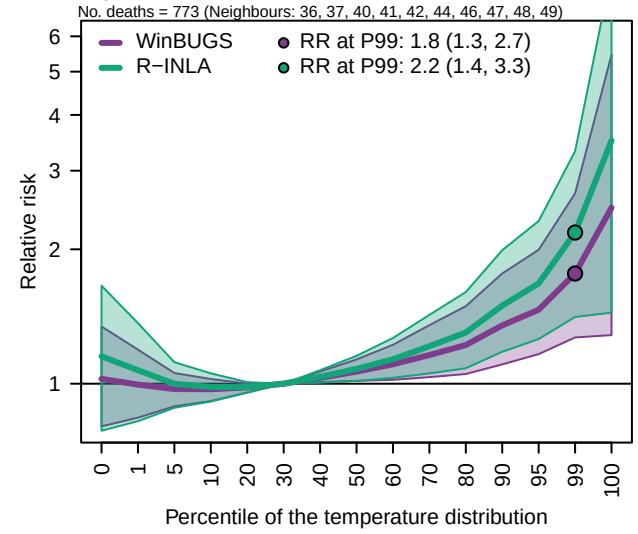
42b) la Clota: Time−series
No. deaths = 19 (Neighbours: 37, 38, 41, 43)



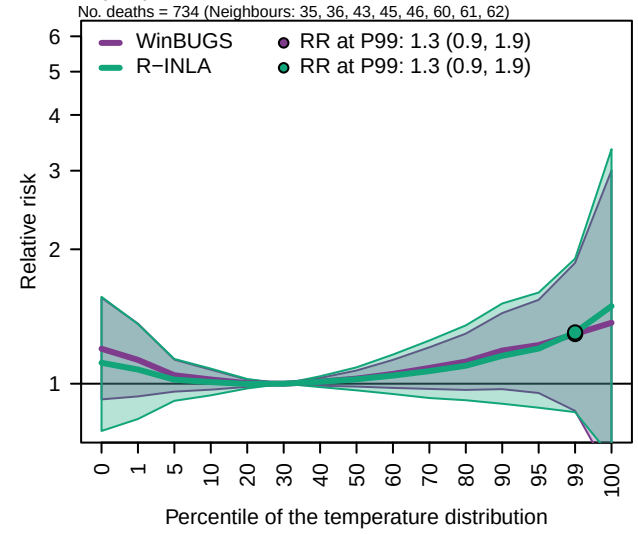
43a) Horta: Case−crossover
No. deaths = 773 (Neighbours: 36, 37, 40, 41, 42, 44, 46, 47, 48, 49)



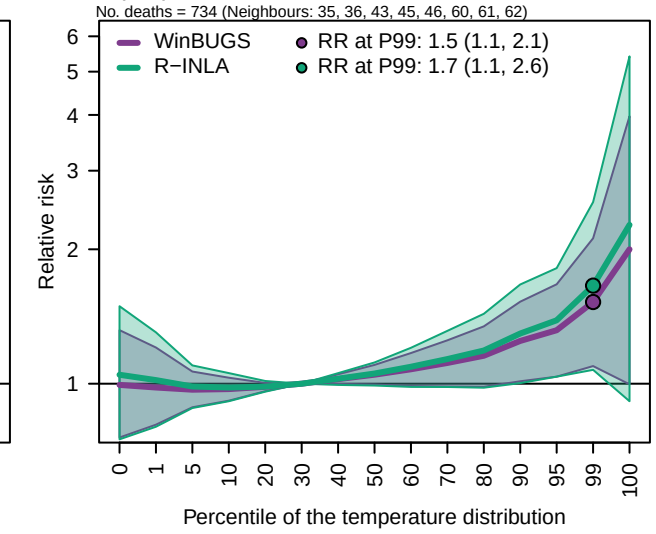
43b) Horta: Time−series
No. deaths = 773 (Neighbours: 36, 37, 40, 41, 42, 44, 46, 47, 48, 49)



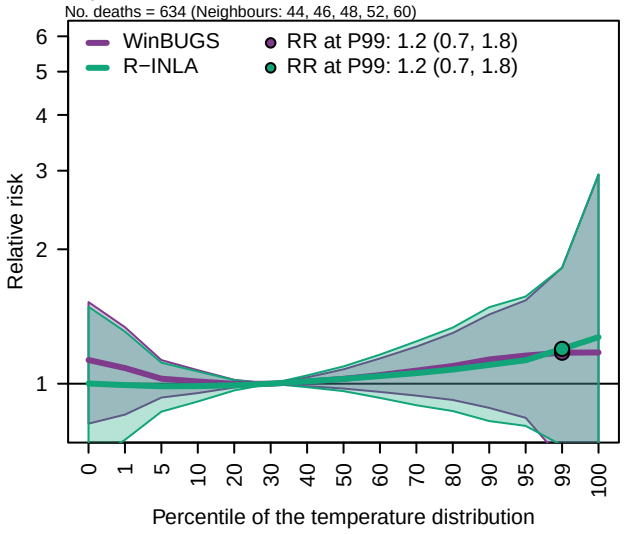
44a) Vilapicina i la Torre Llobeta: Case−crossover
No. deaths = 734 (Neighbours: 35, 36, 43, 45, 46, 60, 61, 62)



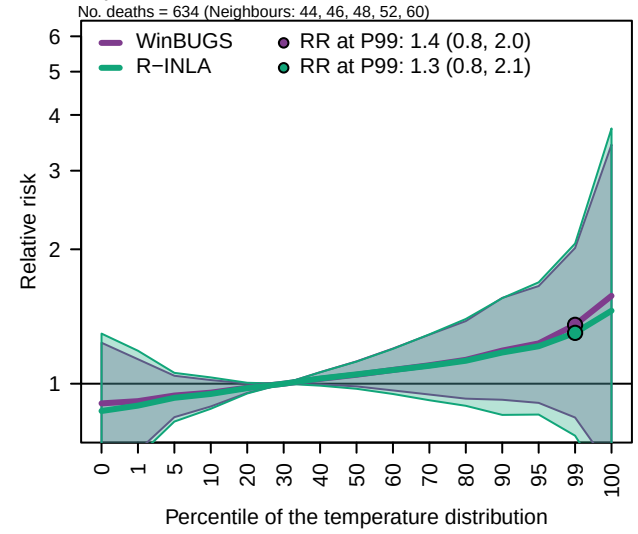
44b) Vilapicina i la Torre Llobeta: Time−series
No. deaths = 734 (Neighbours: 35, 36, 43, 45, 46, 60, 61, 62)



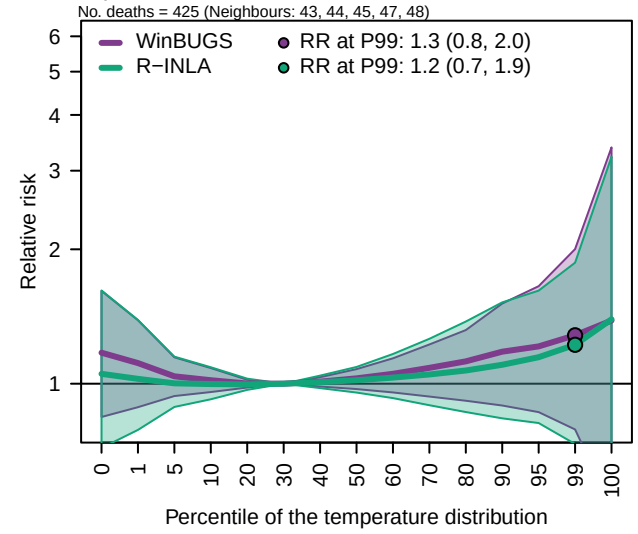
45a) Porta: Case−crossover
No. deaths = 634 (Neighbours: 44, 46, 48, 52, 60)



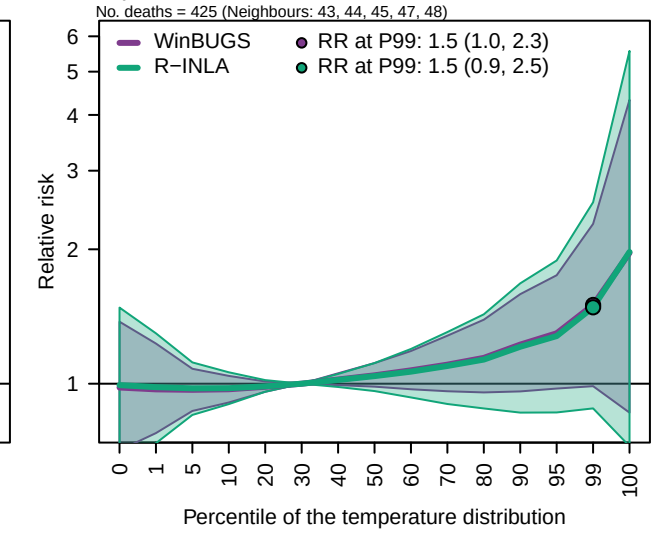
45b) Porta: Time−series
No. deaths = 634 (Neighbours: 44, 46, 48, 52, 60)



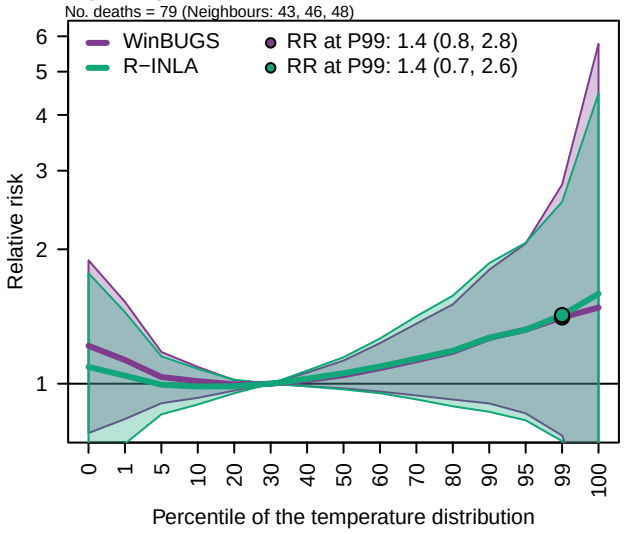
46a) el Turó de la Peira: Case−crossover
No. deaths = 425 (Neighbours: 43, 44, 45, 47, 48)



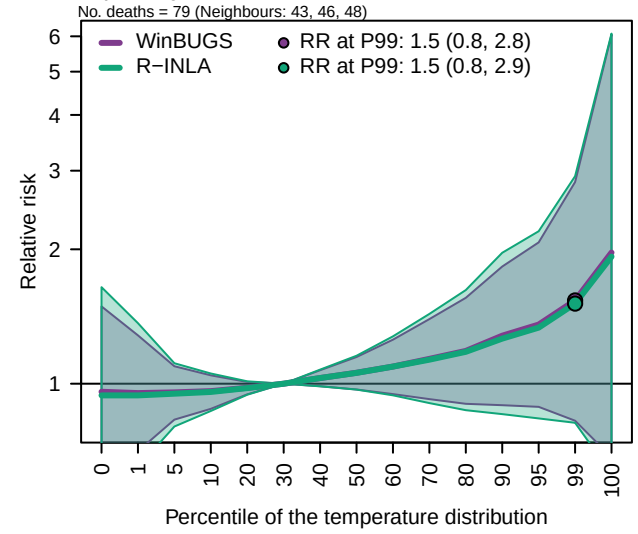
46b) el Turó de la Peira: Time−series
No. deaths = 425 (Neighbours: 43, 44, 45, 47, 48)



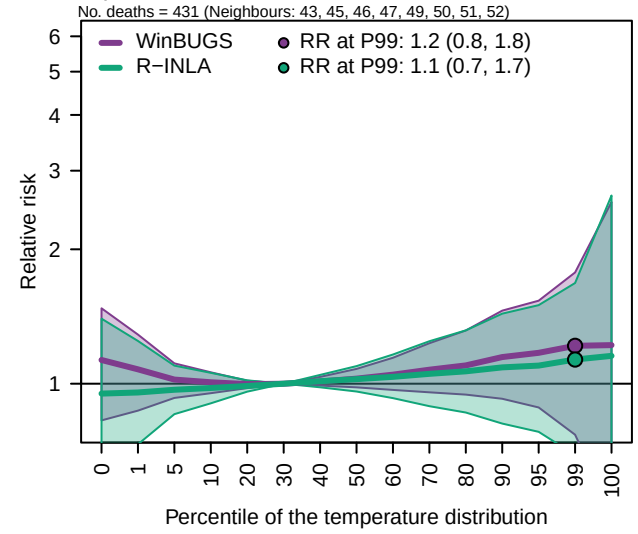
47a) Can Peguera: Case−crossover
No. deaths = 79 (Neighbours: 43, 46, 48)



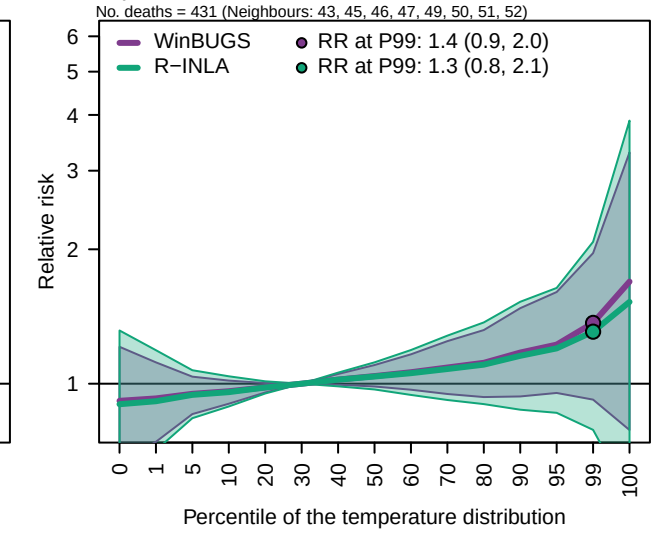
47b) Can Peguera: Time−series
No. deaths = 79 (Neighbours: 43, 46, 48)

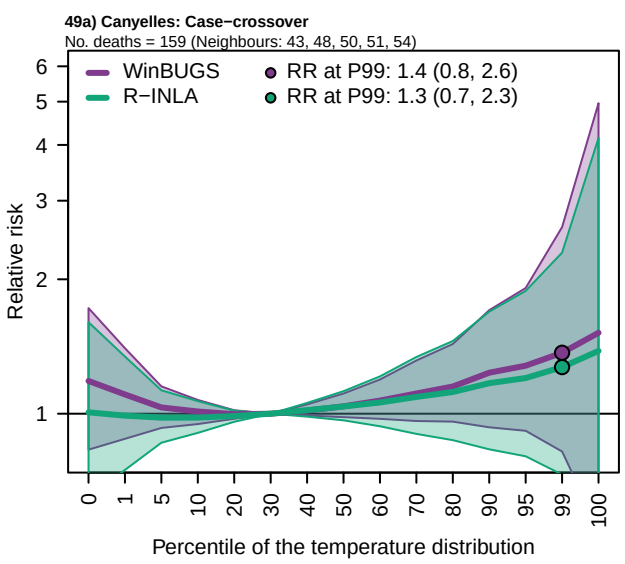


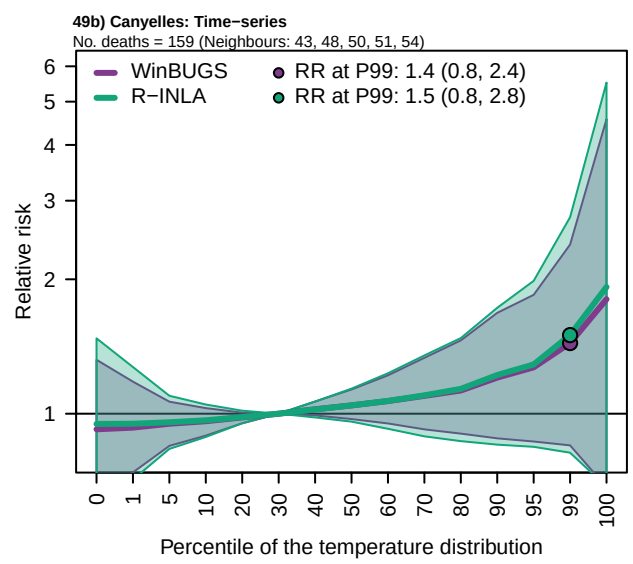
48a) la Guineueta: Case−crossover
No. deaths = 431 (Neighbours: 43, 45, 46, 47, 49, 50, 51, 52)

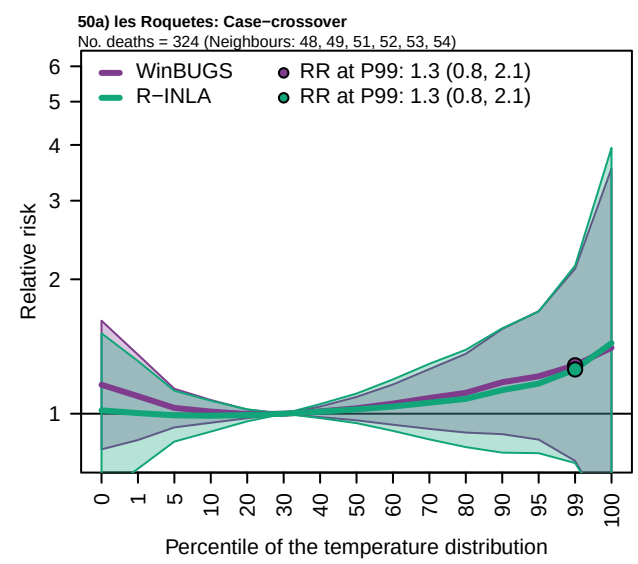


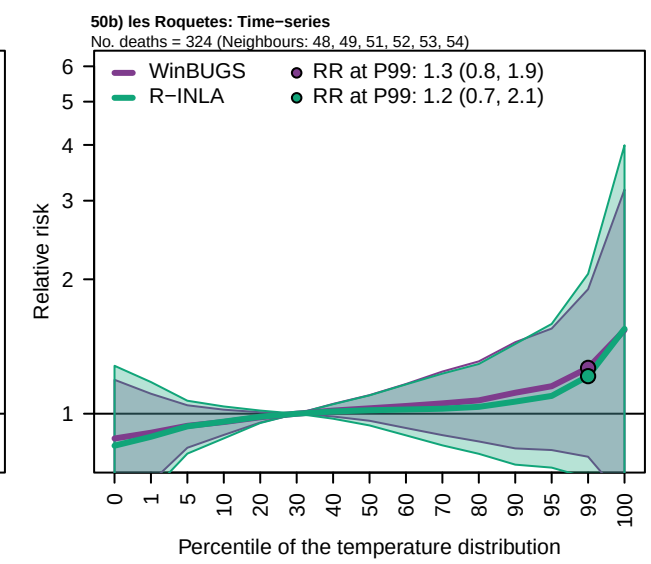
48b) la Guineueta: Time−series
No. deaths = 431 (Neighbours: 43, 45, 46, 47, 49, 50, 51, 52)

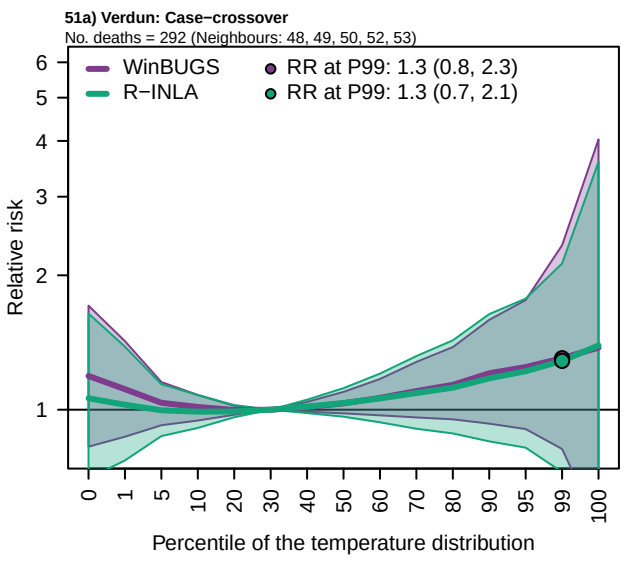


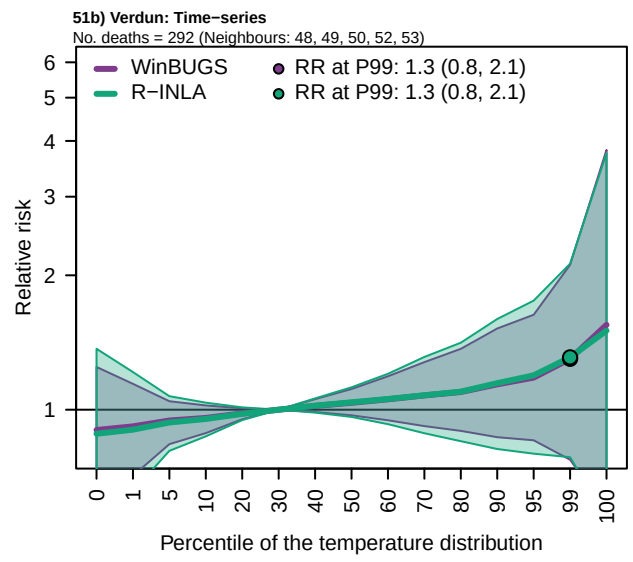

49a) Canyelles: Case−crossover
No. deaths = 159 (Neighbours: 43, 48, 50, 51, 54)
WinBUGS
R−INLA
RR at P99: 1.4 (0.8, 2.6)
RR at P99: 1.3 (0.7, 2.3)
Relative risk
Percentile of the temperature distribution

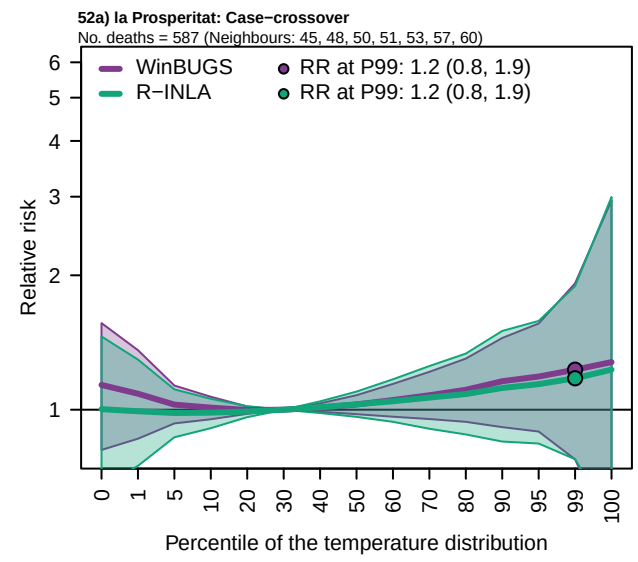

49b) Canyelles: Time−series
No. deaths = 159 (Neighbours: 43, 48, 50, 51, 54)
WinBUGS
R−INLA
RR at P99: 1.4 (0.8, 2.4)
RR at P99: 1.5 (0.8, 2.8)
Relative risk
Percentile of the temperature distribution

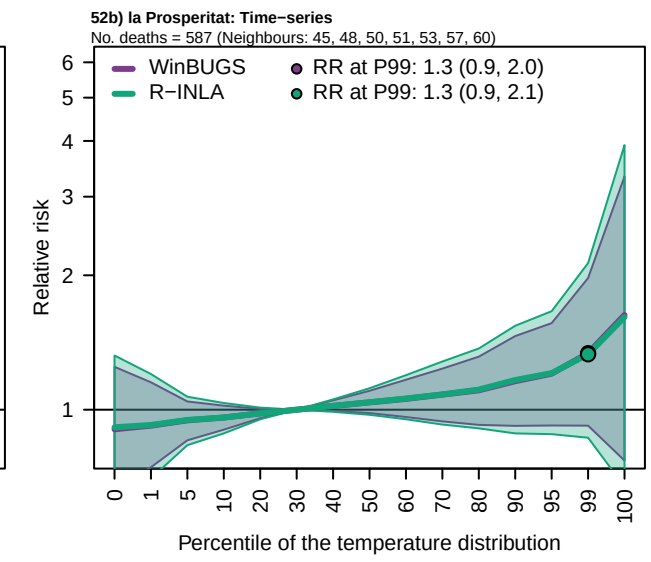

50a) les Roquetes: Case−crossover
No. deaths = 324 (Neighbours: 48, 49, 51, 52, 53, 54)
WinBUGS
R−INLA
RR at P99: 1.3 (0.8, 2.1)
RR at P99: 1.3 (0.8, 2.1)
Relative risk
Percentile of the temperature distribution

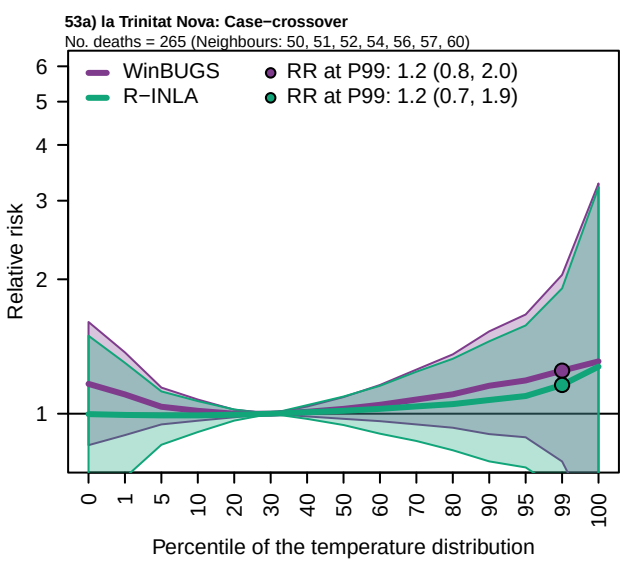

50b) les Roquetes: Time−series
No. deaths = 324 (Neighbours: 48, 49, 51, 52, 53, 54)
WinBUGS
R−INLA
RR at P99: 1.3 (0.8, 1.9)
RR at P99: 1.2 (0.7, 2.1)
Relative risk
Percentile of the temperature distribution

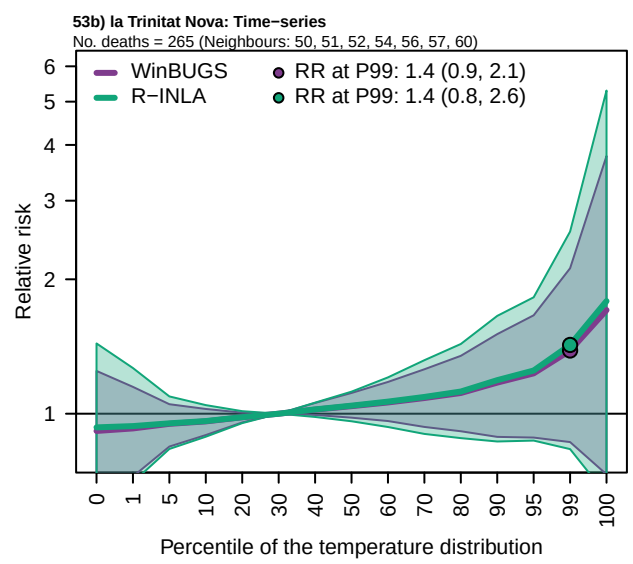

51a) Verdun: Case−crossover
No. deaths = 292 (Neighbours: 48, 49, 50, 52, 53)
WinBUGS
R−INLA
RR at P99: 1.3 (0.8, 2.3)
RR at P99: 1.3 (0.7, 2.1)
Relative risk
Percentile of the temperature distribution

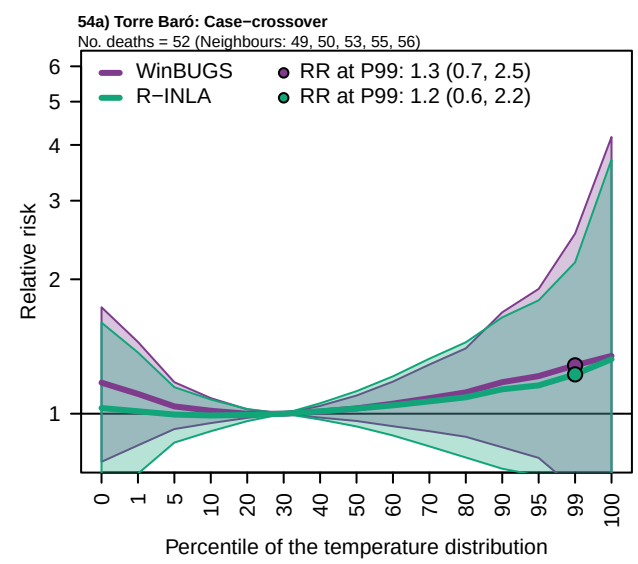

51b) Verdun: Time−series
No. deaths = 292 (Neighbours: 48, 49, 50, 52, 53)
WinBUGS
R−INLA
RR at P99: 1.3 (0.8, 2.1)
RR at P99: 1.3 (0.8, 2.1)
Relative risk
Percentile of the temperature distribution

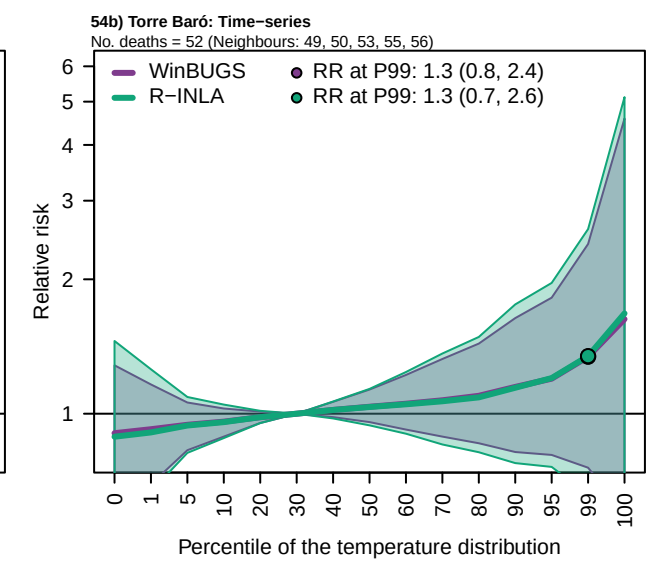

52a) la Prosperitat: Case−crossover
No. deaths = 587 (Neighbours: 45, 48, 50, 51, 53, 57, 60)
WinBUGS
R−INLA
RR at P99: 1.2 (0.8, 1.9)
RR at P99: 1.2 (0.8, 1.9)
Relative risk
Percentile of the temperature distribution

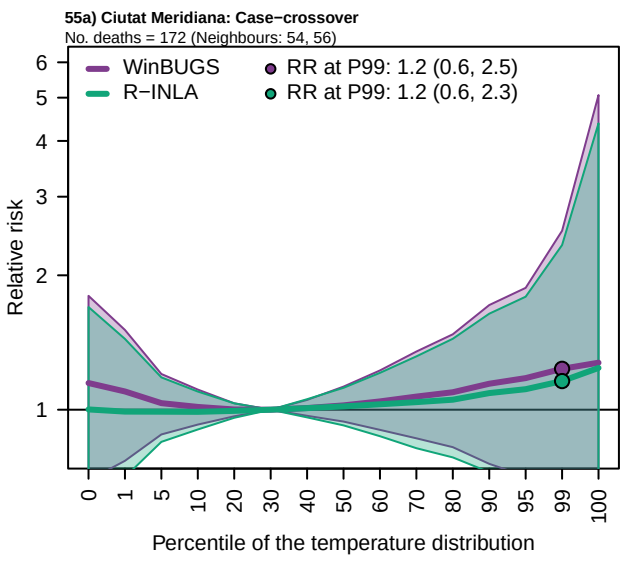

52b) la Prosperitat: Time−series
No. deaths = 587 (Neighbours: 45, 48, 50, 51, 53, 57, 60)
WinBUGS
R−INLA
RR at P99: 1.3 (0.9, 2.0)
RR at P99: 1.3 (0.9, 2.1)
Relative risk
Percentile of the temperature distribution

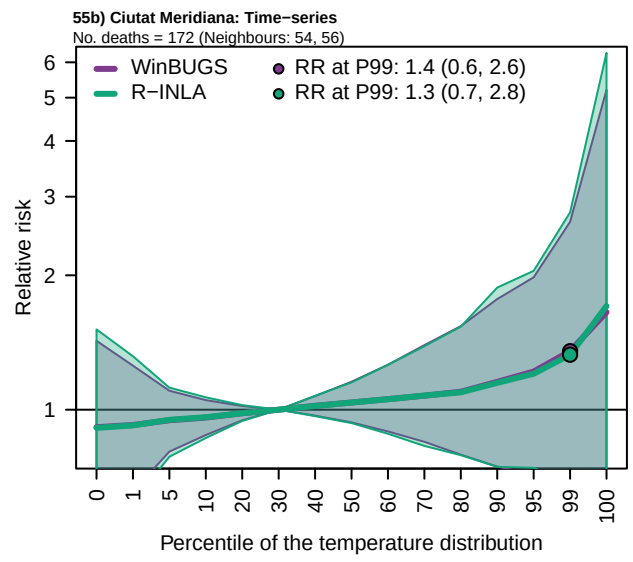

53a) la Trinitat Nova: Case−crossover
No. deaths = 265 (Neighbours: 50, 51, 52, 54, 56, 57, 60)
WinBUGS
R−INLA
RR at P99: 1.2 (0.8, 2.0)
RR at P99: 1.2 (0.7, 1.9)
Relative risk
Percentile of the temperature distribution

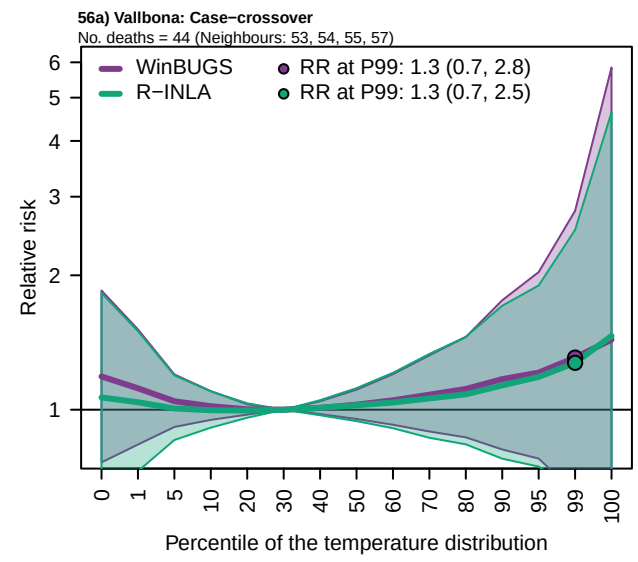

53b) la Trinitat Nova: Time−series
No. deaths = 265 (Neighbours: 50, 51, 52, 54, 56, 57, 60)
WinBUGS
R−INLA
RR at P99: 1.4 (0.9, 2.1)
RR at P99: 1.4 (0.8, 2.6)
Relative risk
Percentile of the temperature distribution

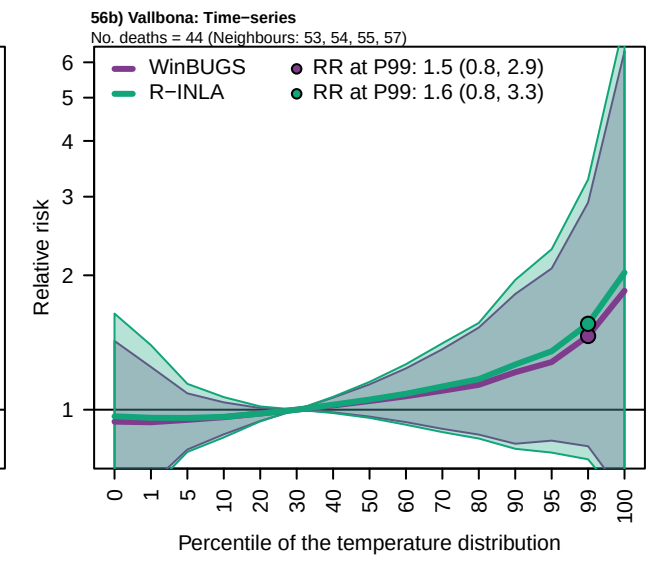

54a) Torre Baró: Case−crossover
No. deaths = 52 (Neighbours: 49, 50, 53, 55, 56)
WinBUGS
R−INLA
RR at P99: 1.3 (0.7, 2.5)
RR at P99: 1.2 (0.6, 2.2)
Relative risk
Percentile of the temperature distribution


54b) Torre Baró: Time−series
No. deaths = 52 (Neighbours: 49, 50, 53, 55, 56)
WinBUGS
R−INLA
RR at P99: 1.3 (0.8, 2.4)
RR at P99: 1.3 (0.7, 2.6)
Relative risk
Percentile of the temperature distribution


55a) Ciutat Meridiana: Case−crossover
No. deaths = 172 (Neighbours: 54, 56)
WinBUGS
R−INLA
RR at P99: 1.2 (0.6, 2.5)
RR at P99: 1.2 (0.6, 2.3)
Relative risk
Percentile of the temperature distribution


55b) Ciutat Meridiana: Time−series
No. deaths = 172 (Neighbours: 54, 56)
WinBUGS
R−INLA
RR at P99: 1.4 (0.6, 2.6)
RR at P99: 1.3 (0.7, 2.8)
Relative risk
Percentile of the temperature distribution


56a) Vallbona: Case−crossover
No. deaths = 44 (Neighbours: 53, 54, 55, 57)
WinBUGS
R−INLA
RR at P99: 1.3 (0.7, 2.8)
RR at P99: 1.3 (0.7, 2.5)
Relative risk
Percentile of the temperature distribution


56b) Vallbona: Time−series
No. deaths = 44 (Neighbours: 53, 54, 55, 57)
WinBUGS
R−INLA
RR at P99: 1.5 (0.8, 2.9)
RR at P99: 1.6 (0.8, 3.3)
Relative risk
Percentile of the temperature distribution

57a) la Trinitat Vella: Case−crossover
No. deaths = 132 (Neighbours: 52, 53, 56, 58, 60)
WinBUGS — RR at P99: 1.4 (0.8, 2.7)
R−INLA — RR at P99: 1.4 (0.8, 2.7)
Relative risk
Percentile of the temperature distribution

57b) la Trinitat Vella: Time−series
No. deaths = 132 (Neighbours: 52, 53, 56, 58, 60)
WinBUGS — RR at P99: 1.4 (0.9, 2.4)
R−INLA — RR at P99: 1.4 (0.8, 2.6)
Relative risk
Percentile of the temperature distribution

58a) Baró de Viver: Case−crossover
No. deaths = 60 (Neighbours: 57, 59, 60)
WinBUGS — RR at P99: 1.3 (0.7, 2.6)
R−INLA — RR at P99: 1.3 (0.7, 2.5)
Relative risk
Percentile of the temperature distribution

58b) Baró de Viver: Time−series
No. deaths = 60 (Neighbours: 57, 59, 60)
WinBUGS — RR at P99: 1.5 (0.8, 2.7)
R−INLA — RR at P99: 1.5 (0.7, 3.2)
Relative risk
Percentile of the temperature distribution

59a) el Bon Pastor: Case−crossover
No. deaths = 260 (Neighbours: 58, 60, 61, 73)
WinBUGS — RR at P99: 1.4 (0.9, 2.6)
R−INLA — RR at P99: 1.4 (0.8, 2.4)
Relative risk
Percentile of the temperature distribution

59b) el Bon Pastor: Time−series
No. deaths = 260 (Neighbours: 58, 60, 61, 73)
WinBUGS — RR at P99: 1.5 (0.9, 2.4)
R−INLA — RR at P99: 1.5 (0.9, 2.7)
Relative risk
Percentile of the temperature distribution

60a) Sant Andreu: Case−crossover
No. deaths = 1191 (Neighbours: 44, 45, 52, 53, 57, 58, 59, 61)
WinBUGS — RR at P99: 1.4 (1.0, 2.0)
R−INLA — RR at P99: 1.4 (0.9, 2.1)
Relative risk
Percentile of the temperature distribution

60b) Sant Andreu: Time−series
No. deaths = 1191 (Neighbours: 44, 45, 52, 53, 57, 58, 59, 61)
WinBUGS — RR at P99: 1.4 (1.1, 2.0)
R−INLA — RR at P99: 1.5 (1.0, 2.2)
Relative risk
Percentile of the temperature distribution

61a) la Sagrera: Case−crossover
No. deaths = 639 (Neighbours: 44, 59, 60, 62, 63, 65, 72, 73)
WinBUGS — RR at P99: 1.4 (1.0, 2.3)
R−INLA — RR at P99: 1.4 (0.9, 2.2)
Relative risk
Percentile of the temperature distribution

61b) la Sagrera: Time−series
No. deaths = 639 (Neighbours: 44, 59, 60, 62, 63, 65, 72, 73)
WinBUGS — RR at P99: 1.5 (1.1, 2.2)
R−INLA — RR at P99: 1.5 (1.0, 2.4)
Relative risk
Percentile of the temperature distribution

62a) el Congrés i els Indians: Case−crossover
No. deaths = 464 (Neighbours: 35, 44, 61, 63)
WinBUGS — RR at P99: 1.2 (0.6, 1.8)
R−INLA — RR at P99: 1.2 (0.7, 1.9)
Relative risk
Percentile of the temperature distribution

62b) el Congrés i els Indians: Time−series
No. deaths = 464 (Neighbours: 35, 44, 61, 63)
WinBUGS — RR at P99: 1.4 (0.8, 2.2)
R−INLA — RR at P99: 1.4 (0.8, 2.3)
Relative risk
Percentile of the temperature distribution

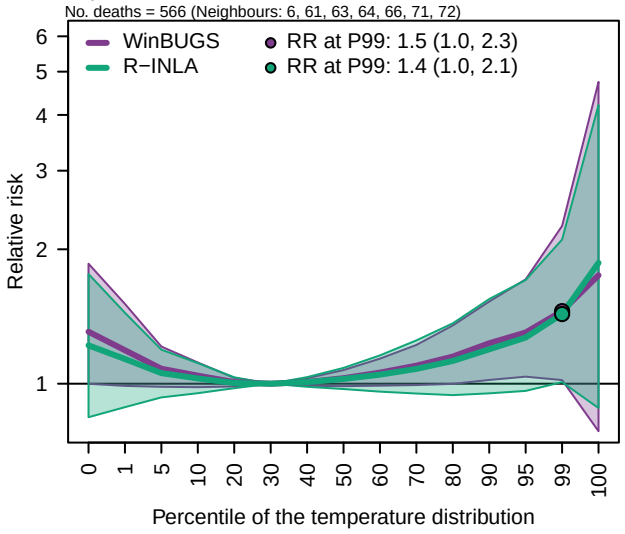
63a) Navas: Case−crossover
No. deaths = 510 (Neighbours: 35, 61, 62, 64, 65)
WinBUGS — RR at P99: 1.3 (0.8, 2.0)
R−INLA — RR at P99: 1.4 (0.9, 2.0)
Relative risk
Percentile of the temperature distribution

63b) Navas: Time−series
No. deaths = 510 (Neighbours: 35, 61, 62, 64, 65)
WinBUGS — RR at P99: 1.6 (1.1, 2.4)
R−INLA — RR at P99: 1.8 (1.1, 2.8)
Relative risk
Percentile of the temperature distribution

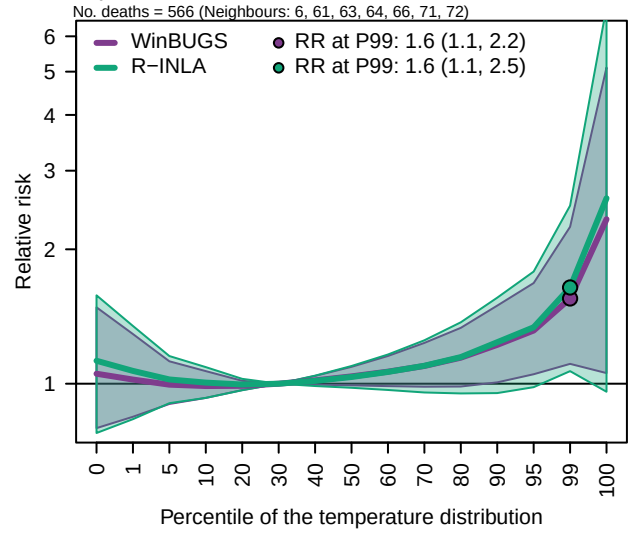
64a) el Camp de l'Arpa del Clot: Case−crossover
No. deaths = 964 (Neighbours: 6, 35, 63, 65)
WinBUGS — RR at P99: 1.4 (0.9, 2.1)
R−INLA — RR at P99: 1.5 (1.0, 2.2)
Relative risk
Percentile of the temperature distribution

64b) el Camp de l'Arpa del Clot: Time−series
No. deaths = 964 (Neighbours: 6, 35, 63, 65)
WinBUGS — RR at P99: 1.7 (1.2, 2.5)
R−INLA — RR at P99: 1.8 (1.2, 2.7)
Relative risk
Percentile of the temperature distribution

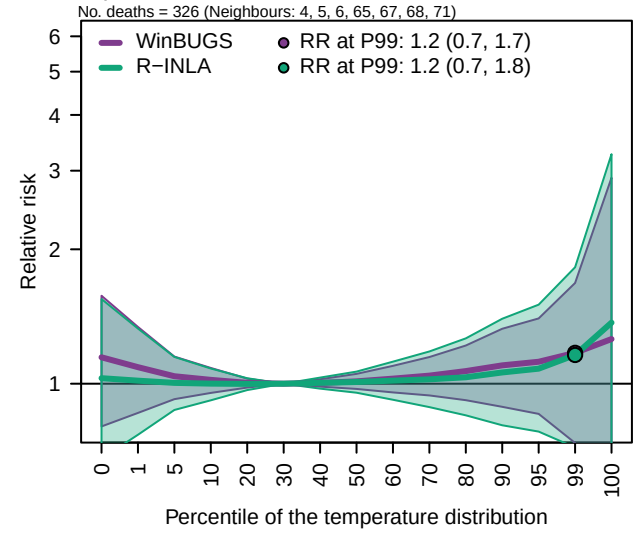
65a) el Clot: Case−crossover
No. deaths = 566 (Neighbours: 6, 61, 63, 64, 66, 71, 72)



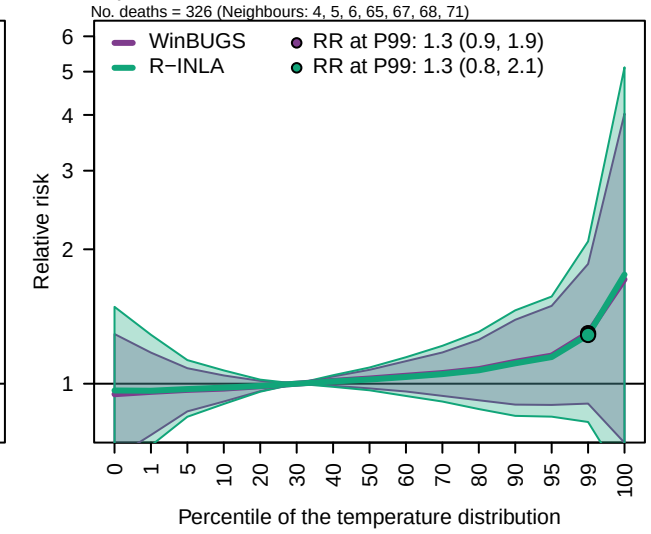
65b) el Clot: Time−series
No. deaths = 566 (Neighbours: 6, 61, 63, 64, 66, 71, 72)



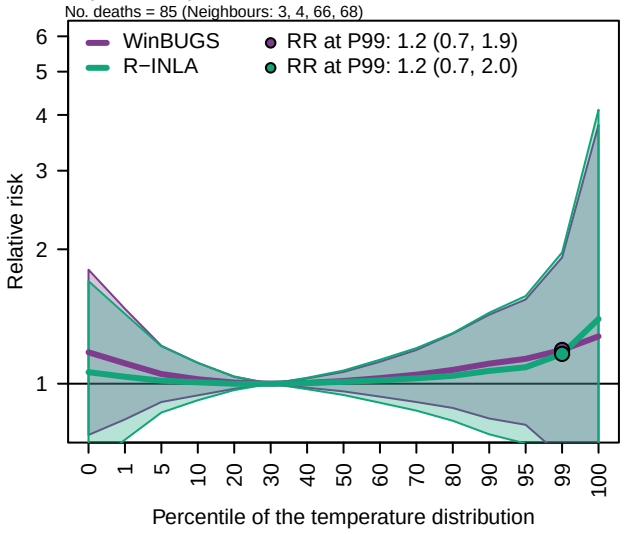
66a) el Parc i la Llacuna del Poblenou: Case−crossover
No. deaths = 326 (Neighbours: 4, 5, 6, 65, 67, 68, 71)



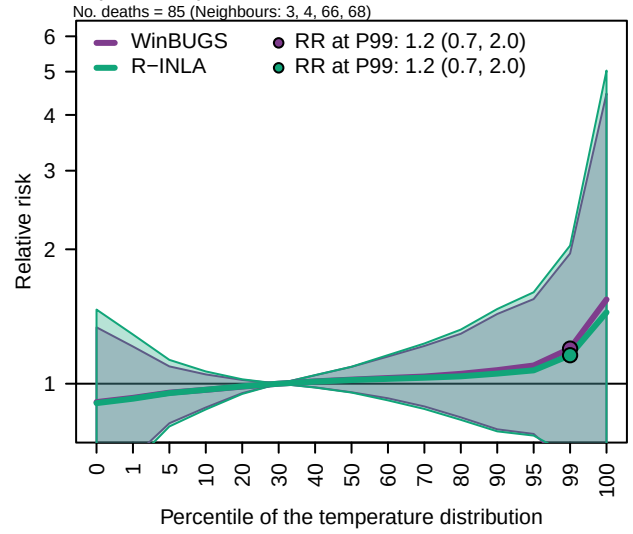
66b) el Parc i la Llacuna del Poblenou: Time−series
No. deaths = 326 (Neighbours: 4, 5, 6, 65, 67, 68, 71)



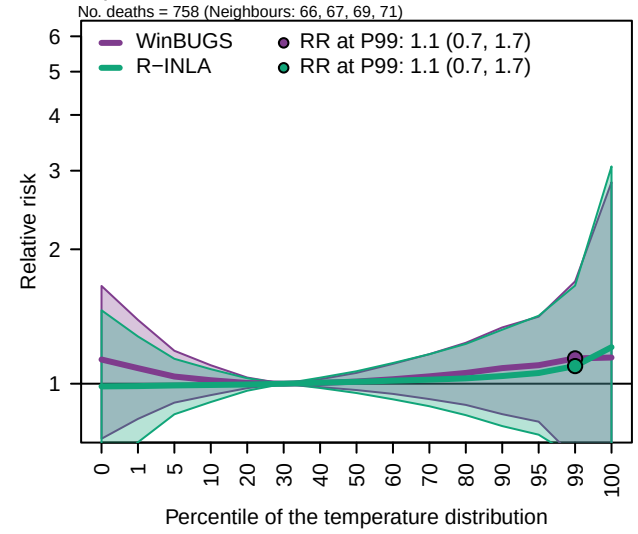
67a) la Vila Olímpica del Poblenou: Case−crossover
No. deaths = 85 (Neighbours: 3, 4, 66, 68)



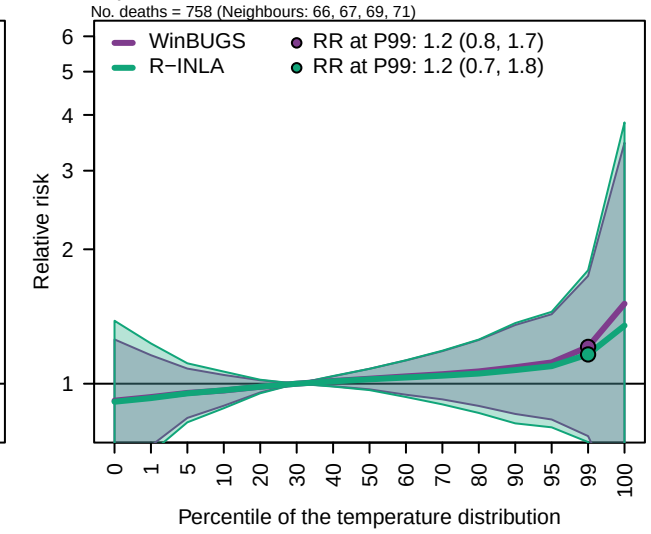
67b) la Vila Olímpica del Poblenou: Time−series
No. deaths = 85 (Neighbours: 3, 4, 66, 68)



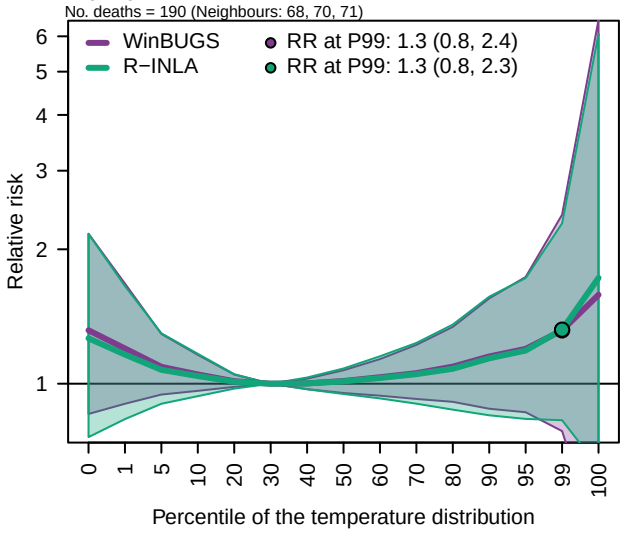
68a) el Poblenou: Case−crossover
No. deaths = 758 (Neighbours: 66, 67, 69, 71)



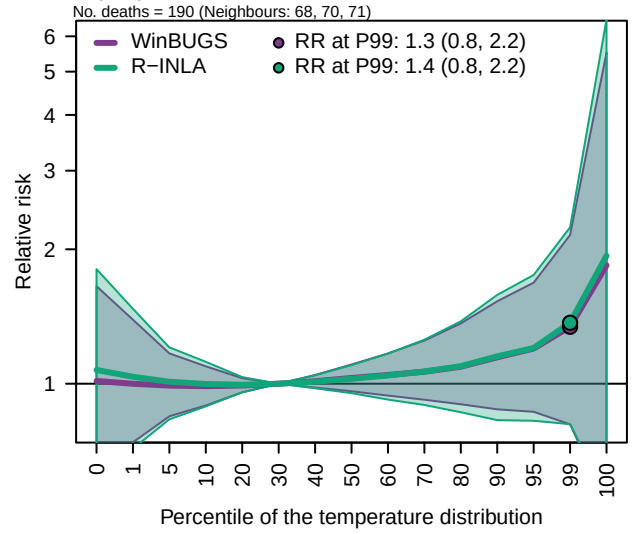
68b) el Poblenou: Time−series
No. deaths = 758 (Neighbours: 66, 67, 69, 71)



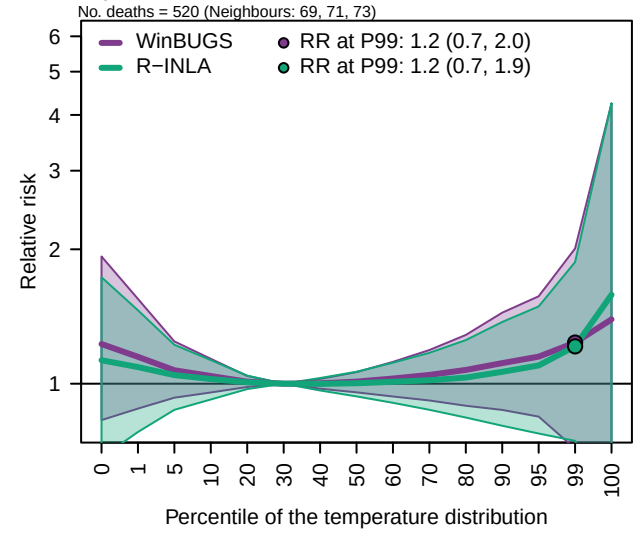
69a) Diagonal Mar i el Front Marítim del Poblenou: Case−crossover
No. deaths = 190 (Neighbours: 68, 70, 71)



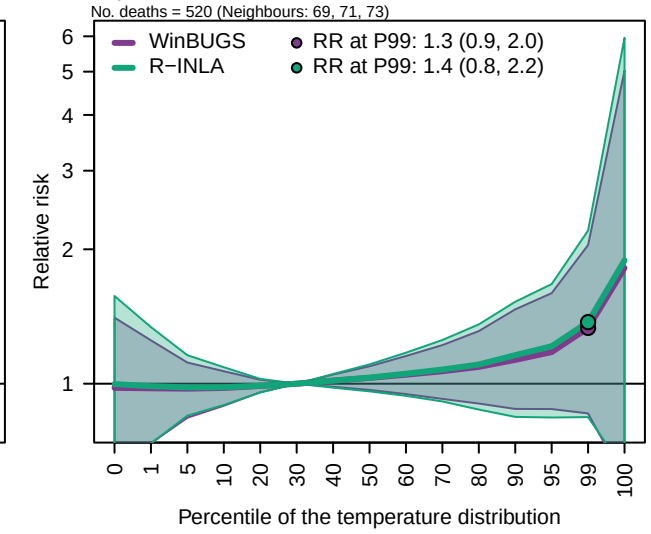
69b) Diagonal Mar i el Front Marítim del Poblenou: Time−series
No. deaths = 190 (Neighbours: 68, 70, 71)



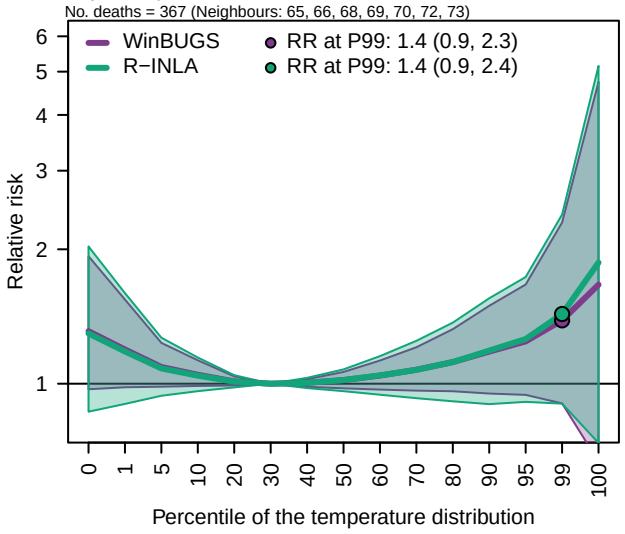
70a) el Besòs i el Maresme: Case−crossover
No. deaths = 520 (Neighbours: 69, 71, 73)



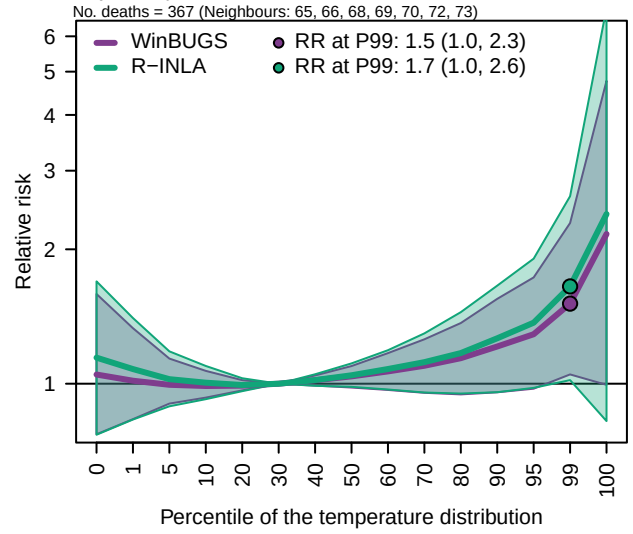
70b) el Besòs i el Maresme: Time−series
No. deaths = 520 (Neighbours: 69, 71, 73)



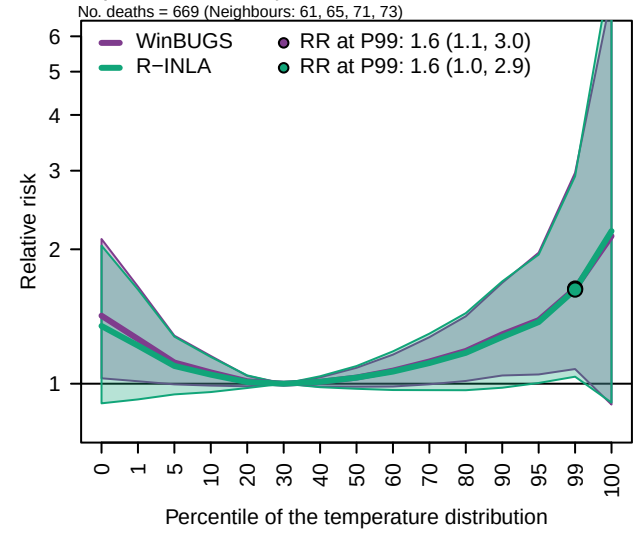
71a) Provençals del Poblenou: Case−crossover
No. deaths = 367 (Neighbours: 65, 66, 68, 69, 70, 72, 73)



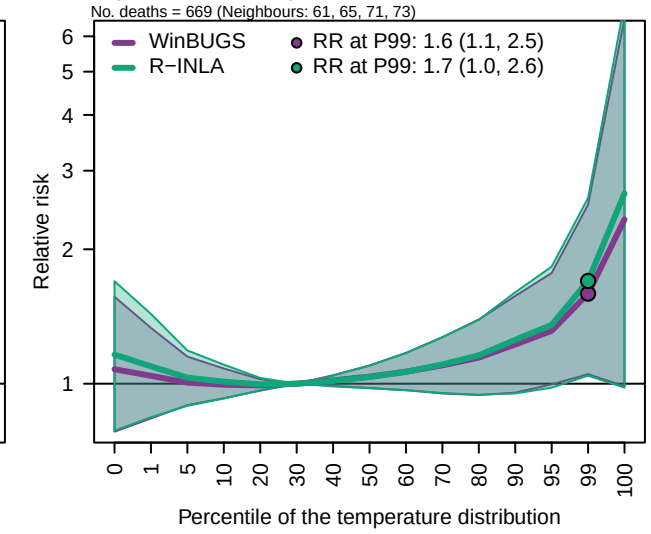
71b) Provençals del Poblenou: Time−series
No. deaths = 367 (Neighbours: 65, 66, 68, 69, 70, 72, 73)

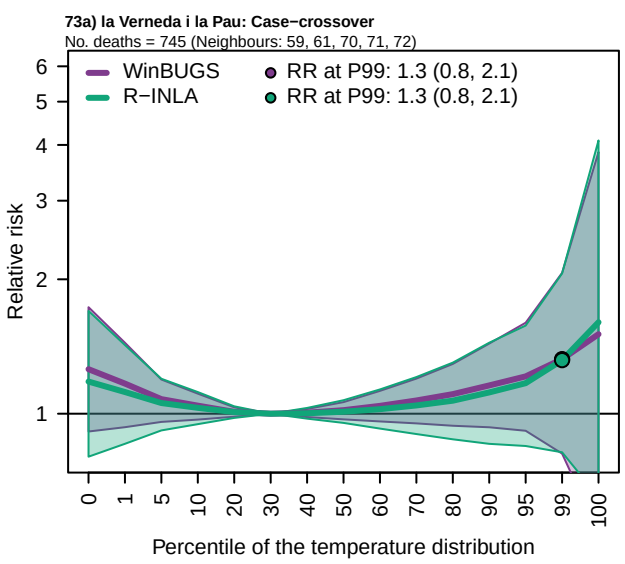


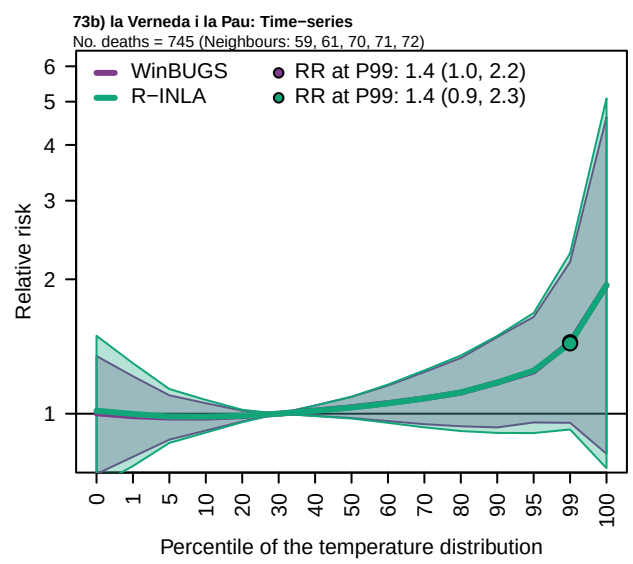
72a) Sant Martí de Provençals: Case−crossover
No. deaths = 669 (Neighbours: 61, 65, 71, 73)



72b) Sant Martí de Provençals: Time−series
No. deaths = 669 (Neighbours: 61, 65, 71, 73)




73a) la Verneda i la Pau: Case−crossover
No. deaths = 745 (Neighbours: 59, 61, 70, 71, 72)
WinBUGS
R−INLA
RR at P99: 1.3 (0.8, 2.1)
RR at P99: 1.3 (0.8, 2.1)
Relative risk
Percentile of the temperature distribution


73b) la Verneda i la Pau: Time−series
No. deaths = 745 (Neighbours: 59, 61, 70, 71, 72)
WinBUGS
R−INLA
RR at P99: 1.4 (1.0, 2.2)
RR at P99: 1.4 (0.9, 2.3)
Relative risk
Percentile of the temperature distribution