Journal of Statistical Software

MMMMMM YYYY, Volume VV, Issue II. *http://www.jstatsoft.org/*

DClusterm: Model-based Detection of Disease Clusters

Virgilio Gómez-Rubio
Universidad de Castilla-La Mancha

Paula Moraga-Serrano
London School of Hygiene
& Tropical Medicine

John Molitor
Oregon State University

Barry Rowlingson
Lancaster University

Abstract

The detection of regions with unusual high risk plays an important role in disease mapping and the analysis of Public Health data. In particular, the detection of groups of areas (i.e., clusters) where the risk is significantly high is often conducted by Public Health authorities.

Many methods have been proposed for the detection of disease clusters, most of them based on moving windows, such as, Kulldorff's Spatial Scan Statistics (SSS). Here we describe a model-based approach for the detection of disease clusters implemented in the **DClusterm** package. Our model-based approach is based on representing a large number of possible clusters by dummy variables and then fitting many genralized linear models to the data wherethese covariates are included one at a time. Cluster detection is done by performing a variable or model selection among all fitted models using different criteria.

Because of our model-based approach, cluster detection can be performed using different types of likelihoods anf latent effects. We cover the detection of spatial and spatio-temporal clusters, as well as how to account for covariates, deal with zero-inflated datasets and overdispersion in the data.

Keywords: disease cluster, spatial statistics, R.

1. Introduction

The analysis of epidemiological data at small area level often involves accounting for possible risks factors and other important covariates using different types of regression models. How-

ever, it is not uncommon that after a number of covariates have been accounted for, residuals show a spatial distribution that defines some groups of areas with unusual high epidemiological risk. Hence, in many ocassions it is not clear whether all spatial risk factors have been included in our model.

Public health data are often aggregated over small administrative areas becasue of confidentiality issues, but it is not uncommon that individual data are available. Generalised Linear Models (GLM,) are a common framework for disease mapping to model aggregated and individual data. GLMs not only model Poisson or Binomial responses, but they can also link the outocome to a linear predictor on the covariates (and, possibly, other effects). However, until recently, it was not clear how to use GLMs to detect clusters of disease, i.e., a group of contiguous areas with significant high risk.

In order to detect disease clusters, probably the most widely used method is the one proposed by Kulldorff (1997). This is called the Spatial Scan Statistic and it will find the most likely cluster. Significance is assessed via a Monte Carlo test using a test statistic based on a likelihood ratio test for the following hypotheses:

$$\begin{aligned} H_0: &\quad \theta_z = \theta_{\bar{z}} \\ H_1: &\quad \theta_z > \theta_{\bar{z}} \end{aligned}$$

Here, z represents a cluster (i.e., a set of contiguous areas), θ_z the relative risk in the cluster and $\theta_{\bar{z}}$ the relative risk outside the cluster. Many different clusters are tested in turn. The most likely cluster is the one with the highest value of the test statistic. Then a Monte Carlo test is used to compute the p-value of the most likely cluster.

In this paper we will summarise the work by several authors that have established a link between GLMs and SSS, so that the detectiopn of disease clusters is approached from a regression point of view. As described later, this will involved fitting many different GLMs for which dummy variables that represent possible clusters are included one at a time. Cluster detection is based on selecting a number of dummy cluster variables using variable selection methods. Furthermore, we will describe how these methods have been implemented in the **DClusterm** package for the R software.

This paper is organised as follows. Section 2 will introduce the link between GLM and SSS. Next, in Section 3 we describe how to extend these ideas to dectect clusters in space and time. The detection of disease clusters for zero-inflated data is discussed in Section 4. Section 5 shows how to include random effects in the detection of disease clusters. A multivariate approach for the detection of disease clusters of two diseases has been included in Section 6. Finally, a discussion and some final remarks are provided in Section 7.

{sec:GLM}

2. Generalised linear models for cluster detection

Jung (2009); Zhang and Lin (2009) provide a explicit link between GLMs and the SSS, and show that the test statistic for a given cluster is equivalent to fitting a Generalised Linear Model using a cluster variable as a predictor. This cluster variable is a dummy variable which is 1 for the areas in the cluster and 0 for the areas outside the cluster.

Firstly, given that we are using GLM's we could include covariates in the model. For example, for a Poisson model with expected counts E_i we could have:

$$O_i \sim Po(E_i\theta_i)$$

$$\log(\theta_i) = \log(E_i) + \alpha + \beta x_i$$

Fitting this model will provide estimates $\hat{\alpha}$ and $\hat{\beta}$. This will account for the (spatial) effects of the covariates. In order to include the cluster variable the effects of the covariates will be keep fixed. Hence, the clusters covariates will be used in a model with fixed coefficients for the covariates:

$$\log(\theta_i) = \log(E_i) + \hat{\alpha} + \hat{\beta} x_i + \gamma_j CLUSTER_j$$

This means that the offset now is $\log(E_i) + \hat{\alpha} + \hat{\beta} x_i$. γ_j is a measure of the difference of the risk in the cluster. We are only interested in clusters whose coefficient is higher than 0 (i.e., increased risk), hence those with a significant negative coefficient will be ignored.

Testing different clusters will produce many different cluster covariates. We can use model selection techniques to select the most important cluster in the area. In particular, the log-likelihood can be used to compare the model with the cluster variable to the null model (i.e., the one with the covariates only). Note that we are interested in clusters with a high risk and, because of that, we are only interested in clustes whose associated coefficient is significantly higher than zero.

Regarding the effect of the covariates, it is possible to perform a cluster dection without considering covariates in the model. Then a cluster detection accouting for the covariates will likely provide a different number of clusters. By comparing the clusters detected in both cases we will be able to find what clusters are linked to underlying risk factors included in the model and what clusters remain unexplained by the covariates. In the examples that we included in this paper we will always consider both scenarios to better understand how cluster detection works with these methods.

Bilancia and Demarinis (2014); Gómez-Rubio, Moraga, and Molitor (2015) describe a similar approach to the detection of disease cluster using Bayesian hierarchical models. The Integrated Nested Laplace Approximation is used in both cases for model fitting as it provides computational benefits over other computationally expensive methods, such as Markov Chain Monte Carlo.

2.1. Leukemia in upstate New York

The `NY8` dataset is avaialble in package `DClusterm` and it provides cases of leukemia in different census tracts in upstate New York. This data set has been analysed by several authors (Waller, Turnbull, Clark, and Nasca 1992; Waller and Gotway 2004). The location of leukemia is thought to be linked to the use of Trichloroethene (TCE) by several companies in the area. Figure 1 shows the Standardised Mortality Ratios of the census tracts and the locations of the industries using TCE.

In order to measure exposure, the inverse of the distance to the nearest TCE site has been used (PEXPOSURE). In addition, two other socioeconomic covariates have been used: the percentage of people aged 65 or more (PCTAGE65P) and the percentage of people who own their home (PCTOWNHOME).

This dataset is included in package **DClusterm** as `NY8`. Hence, our first action is to load some required packages and the dataset itself.

```
> library(DClusterm)
> library(snowfall)
> library(xts)
> data(NY8)
```

A number of cases could not be linked to their actual location and they were distributed uniformly over the study are, making the counts real numbers instead of integers. We have rounded these values as we intend to use a Poisson likelihood for the analysis. Furthermore, expected counts are computed using the overall incidence ratio (total number of cases divided by the total population). Age-sex standarisation is not possible in this case as this information is not available in our dataset.

```
> NY8$Observed <- round(NY8$Cases)
> NY8$Expected <- NY8$POP8 * sum(NY8$Observed)/sum(NY8$POP8)
> NY8$SMR <- NY8$Observed/NY8$Expected
> NY8$x <- coordinates(NY8)[, 1]
> NY8$y <- coordinates(NY8)[, 2]
```

Finally, a `STFDF` object is created to store all the data. Functions in **DClusterm** will take object for space-time data as defined in package **spacetime**. Note that in this case we do not have a truly space-time dataset.

```
> NY8st <- STFDF(as(NY8, "SpatialPolygons"), xts(1, as.Date("1972-01-01")),
+     NY8@data, endTime = as.POSIXct(strptime(c("1972-01-01"),
+         "%Y-%m-%d"), tz = "GMT"))
```

2.2. Cluster detection

Cluster detection with no covariates

First of all, a model with no covariates will be fitted and used as a baseline for model fitting. For example, other models can be compared to this one (for exaple, using the AIC or the log–likelihood) to assess whether they provide a better fit.

```
> ny.m0 <- glm(Observed ~ offset(log(Expected)) + 1, family = "poisson",
+     data = NY8)
```

Cluster detection will use the previous model and new cluster dummy variables will be included, one at a time, to test for a large number of clusters.

Function `DetectClustersModel()` will take the baseline model (using argument `model0`), create the cluster dummy variables and test them in turn. Then, those clusters with a highest significance will be reported.

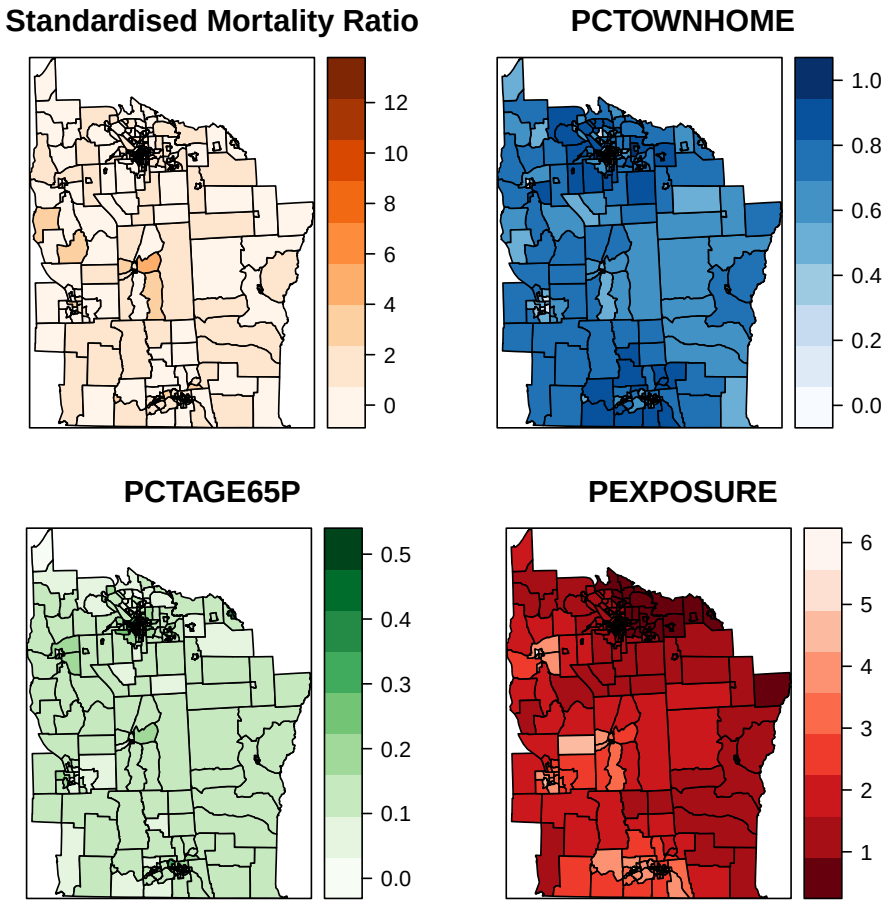


Figure 1: **INCLUDE TCE LOCATIONS** SMR and covariates of the incidence of Leukemia in upstate New York dataset.

{fig:NYmap}

Argument `thegrid` will take a 2-column `data.frame` (with names `x` and y) with the centres of possible clusters. If the grid of cluster centres is not defined, then a rectagular grid is used with a distance between adjacent points defined by argument `step`. Dummy cluster variables are created around these points are created by adding areas to the cluster until a certain percentaje of the population has been reached (defined by argument `fractpop`) or until a certain distance about the centre (defined by argument `radius`). When testing for significant cluster variables, argument `alpha` defines the significance level.

`DetectClustersModel()` can detect spatial and spatio-temporal clusters, that is why its first argument is a space-time object. The type of clusters that are investigated is defined by argument `typeCluster`. In the example we have used `typeCluster = "S"`.

Other options include the number of CPUs to be used to test for clusters in parallel (argument `numCPUS`) and the number of replicates for Monte Carlo tests (argument `R`) if cluster assessment is done by simulation. By default, Monte Carlo tests are not used.

In the following example, to reduce the computational burden, we have only looked for clusters around 5 areas (whose rows in `NY8` are defined in variable `idxcl`). In a real application we

advice the use of all locations (area centroids or actual locations of individual data).

```
> idxcl <- c(120, 12, 89, 139, 146)
> ny.cl0 <- DetectClustersModel(NY8st, thegrid = as.data.frame(NY8)[idxcl,
+     c("x", "y")], fractpop = 0.15, alpha = 0.05, radius = Inf,
+     step = NULL, typeCluster = "S", R = NULL, numCPUS = 4, model0 = ny.m0)
```

Below is a summary of the clusters detected. Dates can be ignored as this is a purely spatial cluster. In the case of spatio-temporal clusters, the dates shown define the temporal range of the cluster. Values `x` and `y` defined the cluster centre, `size` is the number of areas (or individuals) in the cluster, `statistic` represents the point estimate of the associated cluster coefficient Also, note that only clusters with a lower `pvalue` than argument `alpha` are returned. `cluster` indicates whether the cluster is a significant one. Finally, note how detected cluster are order by increasing value of `pvalue`, so that most significant clusters are reported first.

```
> ny.cl0
```

```
           x       y size      minDateCluster      maxDateCluster statistic
11  424728.9 4661404   39 1972-01-01 01:00:00 1972-01-01 01:00:00  8.044846
88  409430.4 4720092    9 1972-01-01 01:00:00 1972-01-01 01:00:00  6.967107
119 404710.7 4768346   24 1972-01-01 01:00:00 1972-01-01 01:00:00  3.254824
          pvalue      risk cluster
11  0.0000604120 0.3916904    TRUE
88  0.0001893208 0.6455613    TRUE
119 0.0107290781 0.4445236    TRUE
```

The centre of the clusters detected are shown in Figure 2. Because of the lack of adjustment for covariates these clusters show regions of high risk based on the raw data (observed and expected counts) alone.

Cluster detection after adjusting for covariates

Similarly, clusters can be detected after adjusting for significant risk factors. First of all, we will fit a Poisson regression with the 3 covariates mentioned earlier. As it can be seen, all three are significant:

```
> ny.m1 <- glm(Observed ~ offset(log(Expected)) + PCTOWNHOME +
+     PCTAGE65P + PEXPOSURE, family = "poisson", data = NY8)
> summary(ny.m1)

Call:
glm(formula = Observed ~ offset(log(Expected)) + PCTOWNHOME +
    PCTAGE65P + PEXPOSURE, family = "poisson", data = NY8)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
```

```
-2.9099  -1.1294  -0.1768   0.6385   3.2426

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.65507    0.18550  -3.531 0.000413 ***
PCTOWNHOME  -0.36472    0.19316  -1.888 0.058998 .
PCTAGE65P    4.05031    0.60559   6.688 2.26e-11 ***
PEXPOSURE    0.15141    0.03165   4.784 1.72e-06 ***
---
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 459.05  on 280  degrees of freedom
Residual deviance: 384.01  on 277  degrees of freedom
AIC: 958.97

Number of Fisher Scoring iterations: 5
```

As the three covariates are significant, the expected number of cases will be different now and the detected clusters may be different in this case. Cluster detection is performed as in the previous example, but now we use the model that adjusts for covariates instead:

```
> ny.cl1 <- DetectClustersModel(NY8st, thegrid = as.data.frame(NY8)[idxcl,
+     c("x", "y")], fractpop = 0.15, alpha = 0.05, typeCluster = "S",
+     R = NULL, numCPUS = 4, model0 = ny.m1)

> ny.cl1

          x       y size      minDateCluster      maxDateCluster statistic
88  409430.4 4720092    9 1972-01-01 01:00:00 1972-01-01 01:00:00  5.861204
119 404710.7 4768346   20 1972-01-01 01:00:00 1972-01-01 01:00:00  3.160591
          pvalue      risk cluster
88  0.0006175202 0.5869176    TRUE
119 0.0119304026 0.4882633    TRUE
```

Figure 2 shows the clusters detected after adjusting for covariates. Compared to the example with no covariate adjustment, one custer has dissappeared. Hence, that cluster has been explained by the effect of the covariates. Another cluster is a bit smaller in size, which means that covariate only explain a small part of it. The most significant cluster remains the same. In all cases, cluster significance has been reduced by the effect of the covariates.

3. Spatio-temporal clusters

{sec:spaceti

Jung (2009) discusses how to extend model-based approaches for the detection of spatial disease clusters to space and time. Gómez-Rubio *et al.* (2015) propose the following model:

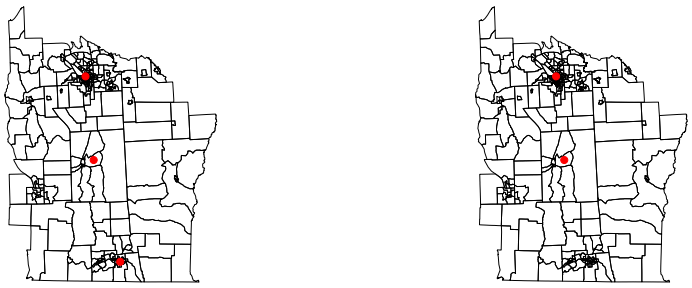


Figure 2: Clusters detected with no covariate adjustment (left) and after adjusting for covariates (right). {fig:NYcl}

$$\log(\mu_{i,t}) = \log(E_{i,t}) + \gamma_j c^{(j)} \quad (1) \quad \{\text{eq:stcluste}$$

where $\mu_{i,t}$ is the mean of area i at time t and $c^{(j)}$ a cluster dummy variable for cluster j.

Note how now data are indexed according to space and time. Dummy cluster variables are defined as in the spatial case, by considering areas in the cluster according to their distance to the cluster centre, for data within a particular time period. When defining a temporal cluster, areas are aggregated using all possible temporal windows up to a predefined temporal range.

3.1. Brain cancer in New Mexico

The `brainNM` dataset (included in **DClusterm**) contains yearly cases of brain cancer in New Mexico from 1973 to 1991 (inclusive) in a **spacetime** object. The data set has been taken from the SatScan website and the area boundaries from the U.S. Census Bureau. In addition, the location of Los Alamos National Laboratory (LANL) has been included (from the Wikipedia). Inverse distance to this site can be used to test for increased risk in the areas around the Laboratory as no other covariates are available.

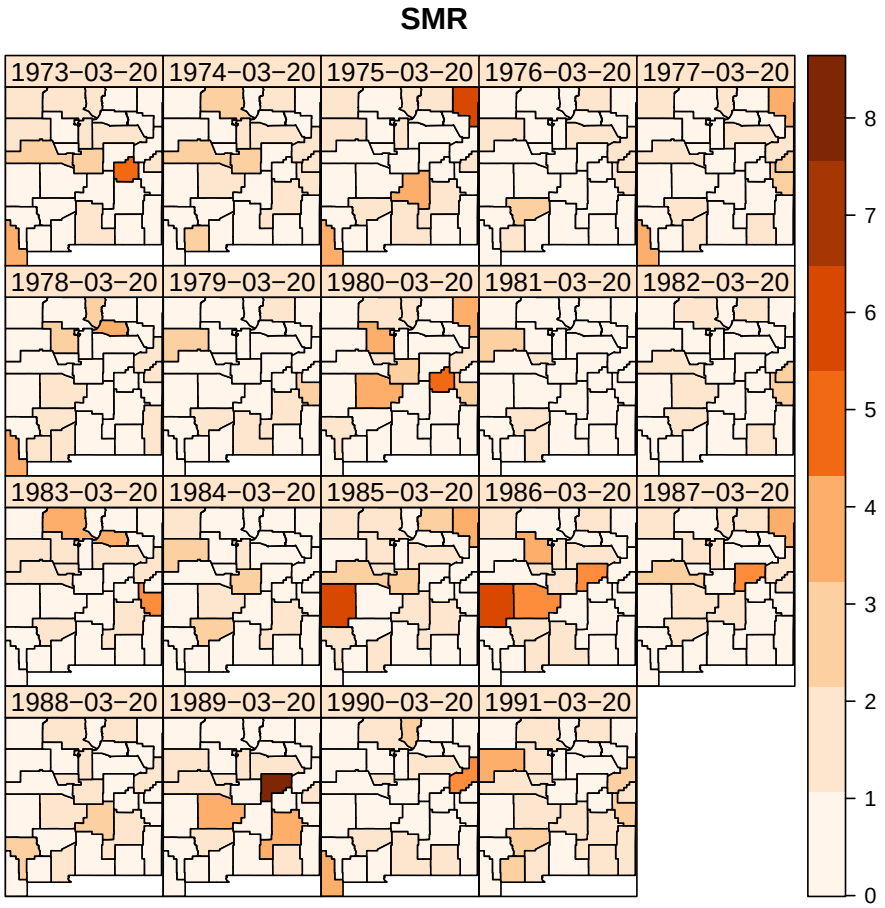
```
> data(brainNM)
```

Expected counts have been obtained using age and sex standardisation over the whole period of time. Hence, yearly differences are likely to be seen when plotting the data. Standardised Mortality Ratios have been plotted in Figure 3.

3.2. Cluster detection

Cluster detection with no covariates

Similarly as in the purely spatial case, a Poisson regression with no covariates will be fitted first:



{fig:NMSMR} Figure 3: Standardised Mortality Ratios of brain cancer in New Mexico.

```
> nm.m0 <- glm(Observed ~ offset(log(Expected)) + 1, family = "poisson",
+     data = brainst)
> summary(nm.m0)


Call:
glm(formula = Observed ~ offset(log(Expected)) + 1, family = "poisson",
    data = brainst)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4874  -0.9998  -0.4339   0.3773   3.1321

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 2.834e-16  2.917e-02       0        1

(Dispersion parameter for poisson family taken to be 1)
```

```
    Null deviance: 631.64  on 607  degrees of freedom
Residual deviance: 631.64  on 607  degrees of freedom
AIC: 1585.6

Number of Fisher Scoring iterations: 5
```

Before proceding with disease cluster detection, we have extracted the centroids of the counties in New Mexico by using function `coordinates()` on the `sp` slot in the `STIDF` object that stores the data.

```
> NM.coords <- coordinates(brainst@sp)
```

Cluster detection with function `DetectClustersModel()` takes now arguments `minDateUser` and `maxDateUser` to define the minimum and maximum times that are considered when looking for clusters. `typeCluster = "ST"` is used to look for spatio-temporal clusters. **ANYTHING ELSE ABOUT HOW S-T CLUSTERS ARE DEFINED?**

** FIXME: Use complete time periord of data for cluster detection

```
> nm.cl0 <- DetectClustersModel(brainst, NM.coords, minDateUser = "1985-01-01",
+     maxDateUser = "1989-01-01", fractpop = 0.15, alpha = 0.05,
+     typeCluster = "ST", R = NULL, numCPUS = 4, model0 = nm.m0)

> nrow(nm.cl0)

[1] 180

> nm.cl0[1:5, ]

             x        y size      minDateCluster      maxDateCluster statistic
0286 -106.3073 35.86930    3 1986-03-20 01:00:00 1988-03-20 01:00:00  7.493492
0496 -105.9761 35.50684    2 1986-03-20 01:00:00 1988-03-20 01:00:00  6.438221
0531 -106.9303 34.00725    9 1985-03-20 01:00:00 1986-03-20 01:00:00  6.378992
0498 -105.9761 35.50684    2 1987-03-20 01:00:00 1988-03-20 01:00:00  6.331113
0288 -106.3073 35.86930    2 1987-03-20 01:00:00 1988-03-20 01:00:00  6.331113
           pvalue      risk cluster
0286 0.0001082553 0.6814588    TRUE
0496 0.0003327442 0.6970405    TRUE
0531 0.0003544929 0.3838756    TRUE
0498 0.0003731179 0.8070901    TRUE
0288 0.0003731179 0.8070901    TRUE
```

Cluster detection after adjusting for covariates

In this case, we will use the inverse of the distance to LANL as a covariate as no other information about the areas is available. Distances have been computed using function `spDistsN1` Given that coordinates are expressed in longitude and latitude great circle distances are used.

```
> dst <- spDistsN1(pts = NM.coords, pt = losalamos, longlat = TRUE)
```

Distances need to be put together in a way that values are available for all time periods. In this case, given that distances do not change over time, a vector is creaeted by repeating the vector of distances as many times as time slots (years) we have in the dataset.

```
> nyears <- length(unique(brainst$Year))
> brainst$IDLANL <- rep(1/dst, nyears)
```

With all this data we are now able to fit a baseline model.

```
> nm.m1 <- glm(Observed ~ offset(log(Expected)) + IDLANL, family = "poisson",
+     data = brainst)
> summary(nm.m1)

Call:
glm(formula = Observed ~ offset(log(Expected)) + IDLANL, family = "poisson",
    data = brainst)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4832  -0.9982  -0.4280   0.3775   3.1424

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.005721   0.029897  -0.191    0.848
IDLANL       0.338194   0.364900   0.927    0.354

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 631.64  on 607  degrees of freedom
Residual deviance: 630.84  on 606  degrees of freedom
AIC: 1586.8

Number of Fisher Scoring iterations: 5
```

Note how now the included covariate is not significant. For illustrative purposes, we will still keep the covariate in our model for the cluster detection. However, non-significant covariates will have a tiny impact on the clusters detected as they will not produce a change in the expected number of cases.

** FIXME: Use complete time periord of data for cluster detection

```
> nm.cl1 <- DetectClustersModel(brainst, NM.coords, fractpop = 0.15,
+     alpha = 0.05, minDateUser = "1985-01-01", maxDateUser = "1989-01-01",
+     typeCluster = "ST", R = NULL, numCPUS = 4, model0 = nm.m1)
```

The number of clusters detected in this case is 179, the same as in the example with no covariates (**CHECK**). By inspecting the five most significant clusters we can observe that they are very similar to the ones detected before:

```
> nm.cl1[1:5, ]
```

```
             x        y size      minDateCluster      maxDateCluster statistic
0286 -106.3073 35.86930    3 1986-03-20 01:00:00 1988-03-20 01:00:00  6.857043
0531 -106.9303 34.00725    9 1985-03-20 01:00:00 1986-03-20 01:00:00  6.468793
0533 -106.9303 34.00725   10 1985-03-20 01:00:00 1988-03-20 01:00:00  6.127863
0498 -105.9761 35.50684    2 1987-03-20 01:00:00 1988-03-20 01:00:00  5.789489
0288 -106.3073 35.86930    2 1987-03-20 01:00:00 1988-03-20 01:00:00  5.789489
           pvalue      risk cluster
0286 0.0002128519 0.6487025    TRUE
0531 0.0003220500 0.3867413    TRUE
0533 0.0004638328 0.2581938    TRUE
0498 0.0006670157 0.7673274    TRUE
0288 0.0006670157 0.7673274    TRUE
```

In order to exploit the output from `DetectClustersModel()`, function `get.stclusters()` will take the data and this output to return a list with the indices of the areas in the cluster. The next example shows how to add a new variable to `brainst` with the space-time regions in the most significant cluster, which is displayed in Figure 4.

```
> stcl <- get.stclusters(brainst, nm.cl0)
> brainst$CLUSTER <- 0
> brainst$CLUSTER[stcl[[1]]] <- 1
```

[sec:zeroinfl]

4. Zero-inflated models for cluster detection

The analysis of rare diseases often involves datasets where there are many areas with zero counts, leading to zero-inflated data. In this situation the Poisson or Binomial likelihoods may not be suitable to fit a model and other distributions for the data should be used. Gómez-Rubio and López-Quílez (2010) discuss this issue and they have extended model-based cluster detection methods to account for zero-inflation.

Four count data, a zero-inflated Poisson could be used. In this case, observed number of cases come from a mixture distribution:

$$Pr(O_i = n_i) = \begin{cases} \pi_i + (1-\pi_i)Po(0|\theta_i E_i) & n_i = 0 \\ (1-\pi_i)Po(n_i|\theta_i E_i) & n_i = 1, 2, \ldots \end{cases}$$

Relative risk θ_i can be modelled using a log-linear model to depend on some relevant risk factors. Also, it is common that all π_i's are taken equal to a single value π.

4.1. Brain cancer in Navarre (Spain)

Ugarte, Ibáñez, and Militino (2006) analyse the incidence of brain cancer in Navarre (Spain). The aggregation level is the health district. Figure 5 shows the Standardised Mortality Ratios.

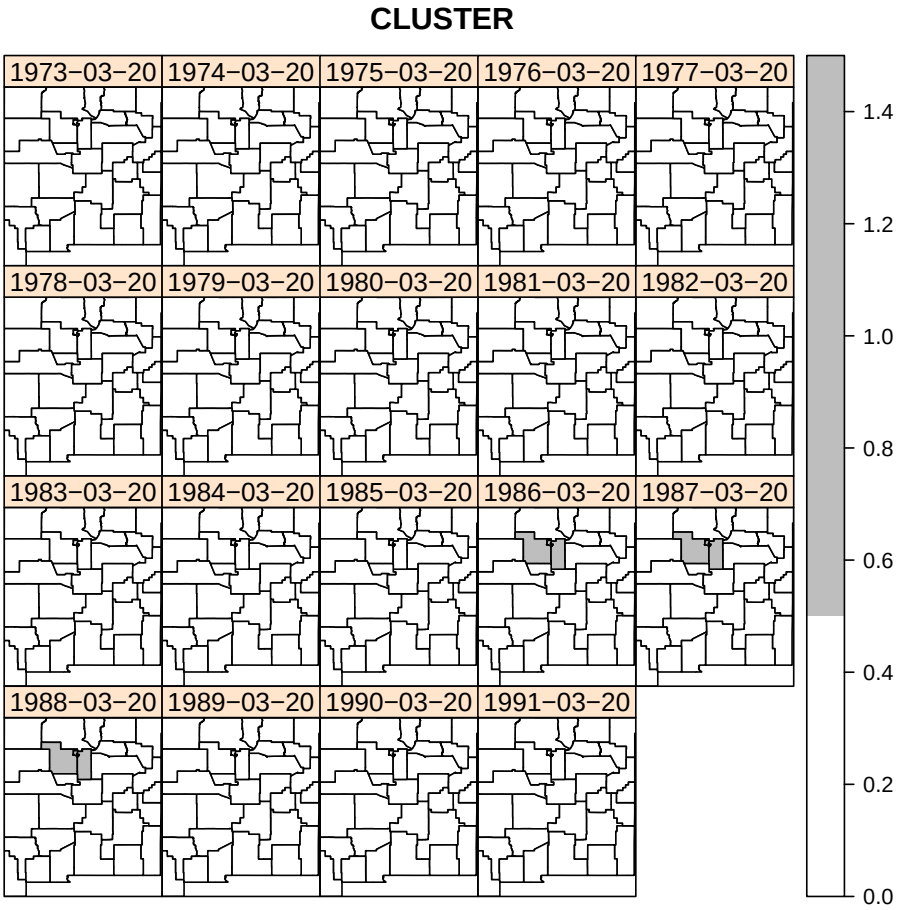


fig:NMcluster}

Figure 4: Spatio-temporal cluster of brain cancer detected in New Mexico.

As it can be seen there are many areas where the SMR is zero because there are no cases in those areas. Ugarte, Ibáñez, and Militino (2004) also assessed a significant zero-inflation of these data compared to a Poisson distribution. For cluster detection, the method implemented in `DClusterm` is similar to the one used in Gómez-Rubio and López-Quílez (2010) for the detection of disease clusters of rare diseases.

4.2. Cluster detection

Before starting our cluster detection methods, we will check the appropriateness of a Poisson distribution for this data. Fitting a log-linear model (with no covariates) gives the following model:

```
> nav.m0 <- glm(OBSERVED ~ offset(log(EXPECTED)) + 1, family = "poisson",
+     data = brainnav)
> summary(nav.m0)

Call:
glm(formula = OBSERVED ~ offset(log(EXPECTED)) + 1, family = "poisson",
```

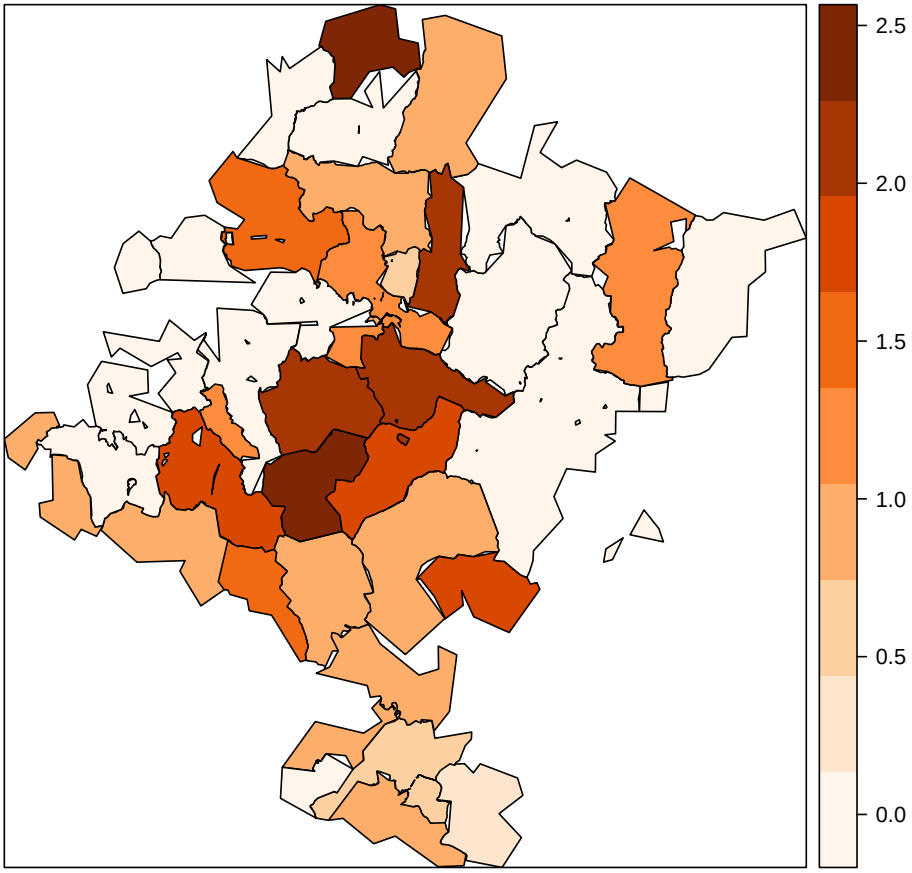


Figure 5: SMR of brain cancer in Navarre (Spain).

{fig:Navarre

```
    data = brainnav)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.5227  -1.4783  -0.3203   0.7042   1.6393

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -7.752e-06  8.805e-02       0        1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 63.733  on 39  degrees of freedom
Residual deviance: 63.733  on 39  degrees of freedom
AIC: 145.02

Number of Fisher Scoring iterations: 5
```

Furthermore, a quasipoisson model has been fit in order to asses any extra-variation in the data:

```
> nav.m0q <- glm(OBSERVED ~ offset(log(EXPECTED)) + 1, family = "quasipoisson",
+     data = brainnav)
> summary(nav.m0q)

Call:
glm(formula = OBSERVED ~ offset(log(EXPECTED)) + 1, family = "quasipoisson",
    data = brainnav)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.5227  -1.4783  -0.3203   0.7042   1.6393

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -7.752e-06  9.703e-02       0        1

(Dispersion parameter for quasipoisson family taken to be 1.214555)

    Null deviance: 63.733  on 39  degrees of freedom
Residual deviance: 63.733  on 39  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 5
```

The dispersion parameter in the previous model seems to be higher than 1, which may mean that the Poisson distribution is not appropriate.

For this reason, and following Ugarte *et al.* (2004), a zero-inflated Poisson model has been fit using function `zeroinfl()` from package **pscl**. Here is the resulting model:

```
> nav.m0zip <- zeroinfl(OBSERVED ~ offset(log(EXPECTED)) + 1 |
+     1, data = brainnav, dist = "poisson", x = TRUE)
> summary(nav.m0zip)

Call:
zeroinfl(formula = OBSERVED ~ offset(log(EXPECTED)) + 1 | 1, data = brainnav,
    dist = "poisson", x = TRUE)

Pearson residuals:
    Min      1Q  Median      3Q     Max
-1.3585 -0.9137 -0.1378  0.7137  1.8091

Count model coefficients (poisson with log link):
            Estimate Std. Error z value Pr(>|z|)
```

```
(Intercept)  0.09347    0.09459   0.988    0.323

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.6158     0.6435  -2.511    0.012 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 9
Log-likelihood: -69.08 on 2 Df
```

Hence, the zero-inflated Poisson model will be used now to detect clusters of disease. As in the example on the New York leukemia dataset, a **spacetime** object will store all the information. The column for the expected counts must be names `Expected`, and this is our first step now. Note also that, because only one time period is considered, data will have a single value and it is the 1st of January of 1990.

```
> brainnav$Expected <- brainnav$EXPECTED
> brainnavst <- STFDF(as(brainnav, "SpatialPolygons"), xts(1, as.Date("1990-01-01")),
+     as(brainnav, "data.frame"), endTime = as.POSIXct(strptime(c("1990-01-01"),
+         "%Y-%m-%d"), tz = "GMT"))
```

Function `DetectClustersModel()` will perform the cluster detection using a `zeroinfl` model. This provides a very flexible way of handling different types of models in R for cluster detection.

```
> nav.cl0 <- DetectClustersModel(brainnavst, coordinates(brainnav),
+     fractpop = 0.25, alpha = 0.05, typeCluster = "S", R = NULL,
+     numCPUS = 4, model0 = nav.m0zip)
```

The output will show the following clusters:

```
> nav.cl0

          x       y size      minDateCluster      maxDateCluster statistic
31 596886.8 4710520    4 1990-01-01 01:00:00 1990-01-01 01:00:00  2.520092
30 611795.5 4713762    3 1990-01-01 01:00:00 1990-01-01 01:00:00  2.016942
       pvalue      risk cluster
31 0.02476587 0.5987255    TRUE
30 0.04459518 0.6139100    TRUE
```

As it can be seen, two clusters (with a p-value lower than 0.05) are detected. However, they overlap and we will just consider the one with the lowest p-value, which is shown in Figure 6.

An index for the areas in each of the detected cluster can be obtained with function `knbinary()`. This function will return a `data.frame` with all the dummy cluster variables, i.e., the `data.frame` will have as many columns as clusters and a number of rows equal to the number of areas. Entries will be 1 if an areas is in a given cluster and 0 otherwise. This indices can be used for

a number of analyses, such as checking whether two clusters overlap or computing the number of times an area is included in a cluster. In the follwing example we obtain the representation of all the clusters detected and the first one, the most significant, is added as a new column to the original `SpatialPolygonsDataFrame` to be displayed in Figure 6.

```
> nav.clusters <- knbinary(brainnav, nav.cl0)
> brainnav$CLUSTER <- as.factor(nav.clusters[, 1])
> levels(brainnav$CLUSTER) <- c("", "CLUSTER")
```

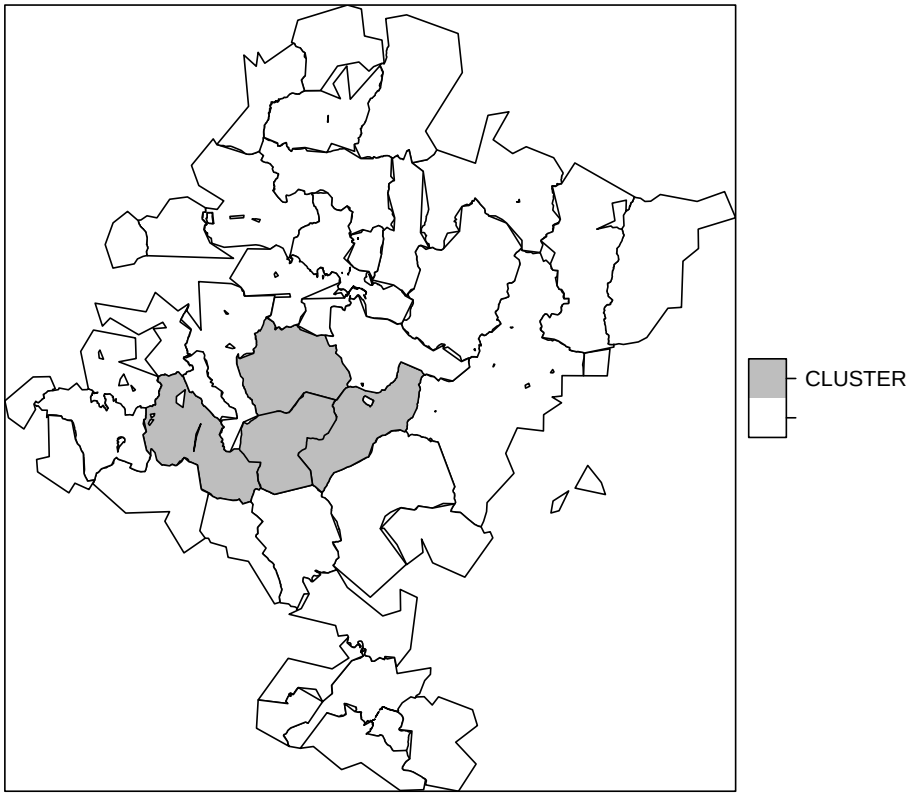


Figure 6: Cluster of brain cancer detected in Navarre (Spain). {fig:Navarre

5. Mixed-effects models for cluster detection {sec:mixed}

Mixed-effects can be incorporated into our models to account for unmeasured risk factors. Cluster detection will be performed as usual, but we should keep in mind that by including random effects and dummy cluster covariates there may be a clash between the two. By using dummy variables we are intentionally looking for unexplained spatial variation in the data. Hence, random effects should aim at modelling a different structure.

Random effects are particularly useful to model over-dispersion in count data. For the Poisson case, this will mean that the realtive risk can be modelled as:

$$\log(\theta_i) = \log(E_i) + \alpha + \beta x_i + \gamma_j c_i^{(j)} + u_i \quad (2)$$
$$u_i \sim N(0, \sigma_u^2) \quad (3)$$

where u_i represents a random effect Normally distributed with zero mean and variance σ_u^2. Note that random effects can be defined to be spatially correalted, as suggested by (Bilancia and Demarinis 2014). However, this can produce a clash between the dummy cluster variables and the random effects.

5.1. Leukemia in upstate New York

We go back to the example on the leukemia incidence in upstate New York to show how models can include random effects and, at the same time, detect disease clusters. In this particular example, random effects will be important in order to reflect any over-dispersion present in the data. For this reason, our first step here is to test the data for over-dispersion using Dean's P_B and P'_B score tests (see, , for details). These two tests have been implemented in functions `DeanB()` and `DeanB2()` in the **DCluster** package. They both take a `glm` object and perform the score tests:

```
> DeanB(ny.m0)

        Dean's P_B test for overdispersion

data:  ny.m0
P_B = 5.5755, p-value = 1.234e-08
alternative hypothesis: greater

> DeanB2(ny.m0)

        Dean's P'_B test for overdispersion

data:  ny.m0
P'_B = 5.6233, p-value = 9.368e-09
alternative hypothesis: greater
```

From the results, it is clear that when no covariates are included data are clearly over-dispersed. Hence, a Poisson distribution will not be appropriate to model the observed counts in each tract.

The same tests applied to the model with covariates produce a similar result:

```
> DeanB(ny.m1)

        Dean's P_B test for overdispersion
```

```
data:  ny.m1
P_B = 2.0145, p-value = 0.02198
alternative hypothesis: greater

> DeanB2(ny.m1)

        Dean's P'_B test for overdispersion

data:  ny.m1
P'_B = 2.2391, p-value = 0.01257
alternative hypothesis: greater
```

Although p-values have increased, they are both small and we may still consider that data are over-dispersed. Hence, we will aim at detecting clusters using a Poison regression with independent random effects to account for track-level heterogeneity.

5.2. Cluster detection with no covariates

```
> ny.mm0 <- glmer(Observed ~ offset(log(Expected)) + (1 | AREANAME),
+     data = as(NY8, "data.frame"), family = "poisson")
> summary(ny.mm0)

Generalized linear mixed model fit by maximum likelihood (Laplace
  Approximation) [glmerMod]
 Family: poisson  ( log )
Formula: Observed ~ offset(log(Expected)) + (1 | AREANAME)
   Data: as(NY8, "data.frame")

     AIC      BIC   logLik deviance df.resid
  1010.8   1018.1   -503.4   1006.8      279

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.1185 -0.8799 -0.2617  0.7784  5.0263

Random effects:
 Groups   Name        Variance Std.Dev.
 AREANAME (Intercept) 0.2111   0.4594
Number of obs: 281, groups:  AREANAME, 64

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.2410     0.1051  -2.293   0.0219 *
---
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1
```

FIXME: glmer()-returned objects need to be added to glmAndZIP.iscluster()

```
> ny.clmm1 <- DetectClustersModel(NY8st, thegrid = as.data.frame(NY8)[idxcl,
+     c("x", "y")], fractpop = 0.15, alpha = 0.05, typeCluster = "S",
+     R = NULL, numCPUS = 4, model0 = ny.mm0)
```

5.3. Cluster detection with covariates

{sec:bivar}

6. Bivariate models for cluster detection

{sec:disc}

7. Discussion

References

Bilancia M, Demarinis G (2014). "Bayesian scanning of spatial disease rates with integrated nested Laplace approximation (INLA)." *Statistical Methods & Applications*, **23**(1), 71–94. ISSN 1618-2510. doi:10.1007/s10260-013-0241-8. URL http://dx.doi.org/10.1007/s10260-013-0241-8.

Gómez-Rubio V, López-Quílez A (2010). "Statistical methods for the geographical analysis of rare diseases." *Advances in experimental medicine and biology*, **686**, 151–171.

Gómez-Rubio V, Moraga P, Molitor J (2015). "Fast Bayesian classification for disease mapping and the detection of disease clusters." *Submitted for publication*.

Jung I (2009). "A generalized linear models approach to spatial scan statistics for covariate adjustment." *Statistics in Medicine*, **28**(7), 1131–1143.

Kulldorff M (1997). "A Spatial Scan Statistic." *Communications in Statistics — Theory and Methods*, **26**(6), 1481–1496.

Ugarte MD, Ibáñez B, Militino AF (2004). "Testing for Poisson Zero Inflation in Disease Mapping." *Biometrical Journal*, **46**(5), 526–539.

Ugarte MD, Ibáñez B, Militino AF (2006). "Modelling risks in disease mapping." *Statistical Methods in Medical Research*, **15**, 21–35.

Waller L, Turnbull B, Clark L, Nasca P (1992). "Chronic disease surveillance and testing of clustering of disease and exposure: application to leukemia incidence in TCE-contamined dumpsites in upstate New York." *Environmetrics*, **3**, 281–300.

Waller LA, Gotway CA (2004). *Applied Spatial Statistics for Public Health Data*. John Wiley & Sons, Hoboken, New Jersey.

Zhang T, Lin G (2009). "Spatial scan statistics in loglinear models." *Computational Statistics and Data Analysis*, **53**(8), 2851–2858.

Affiliation:

Virgilio Gómez-Rubio
Department of Mathematics
School of Industrial Engineering
University of Castilla-La Mancha
02071 Albacete, Spain
E-mail: virgilio.gomez@uclm.es
URL: http://www.uclm.es/profesorado/vgomez

Paula Moraga-Serrano
London School of Hygiene & Tropical Medicine
Keppel Street
WC1E 7HT London, United Kingdom
E-mail: paula.moraga-serrano@lshtm.ac.uk
URL: http://www.lshtm.ac.uk/aboutus/people/moraga-serrano.paula

John Molitor
College of Public Health and Human Sciences
Oregon State University
Corvallis, Oregon 97331, United States
E-mail: John.Molitor@oregonstate.edu
URL: http://health.oregonstate.edu/people/molitor-john

Barry Rowlingson
Lancaster Medical School
Furness Building
Lancaster University
Bailrigg, Lancaster LA1 4YG, United Kingdom
E-mail: b.rowlingson@lancaster.ac.uk
URL: http://www.lancaster.ac.uk/fhm/about-us/people/barry-rowlingson

Journal of Statistical Software http://www.jstatsoft.org/
published by the American Statistical Association http://www.amstat.org/
Volume VV, Issue II *Submitted:* yyyy-mm-dd
MMMMMM YYYY *Accepted:* yyyy-mm-dd