Mapping spatio-temporal patterns of disabled people in emergencies: A Bayesian approach

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Abstract

Emergency management can greatly benefit from understanding the spatio-temporal distribution of individual population groups as this will optimise the allocation of resources and personnel needed in case of an emergency caused by a disaster. This is especially true for people with a disability as they tend to be overlooked by emergency officials. This is generally approached statically using census data, not taking into account the dynamics of disabled peoples concentrations throughout space-time as exhibited in large metropolitan areas such as London. Transport data collected by automatic fare collection methods (such as Transport for London's Oyster card scheme) combined with accessibility covariates (number of opportunities/destinations within an areal unit) have the potential of being a good source for describing the distribution of this concentration. The aim of this study is to explore these datasets for use within the scope as described above. The paper attempts to model the distribution using discrete spatio-temporal variation methods. More specifically, it uses Poisson spatio-temporal generalised linear models built within a Bayesian hierarchical modelling framework, ranging from simple to more complex ones, while taking into account the spatio-temporal interactions that emerge between the space-time units. The performance of the resulting models in terms of their ability to explain the effects of the covariates as well as predicting future disabled peoples counts were compared relative to each other using the deviance information criterion and posterior predictive check criterion. Analysis of the results revealed a distinct spatio-temporal pattern of disabled users for Oyster card datasets, which deviates from the transportation habits of the rest of population. The effect of the chosen covariates diminishes as model's complexity increases, giving rise to patterns that could potentially be explained by including sociological aspects in the models.

1. Introduction

Emergency management can greatly benefit from understanding the spatio-temporal distribution of individual population groups as this will optimize the allocation of resources and personnel needed in case of an emergency caused by a disaster. This is especially true for people with a disability as they tend to be overlooked by emergency officials (Kailes & Enders 2007; Twigg et al. 2011; McGuire et al. 2007; Rooney &

White 2007). The task of identifying the potential number of disabled people involved in an emergency is commonly approached statically using census data (Church & Cova 2000), or by the creation and maintenance of disabled people's registration lists (Metz et al. 2002; Norwood 2011; HMGovernment 2008). These approaches fail to account for the dynamics of disabled people's concentrations throughout space-time as exhibited in large metropolitan areas such as London. Transport data collected by automatic fare collection methods have the potential to be a good source for describing the distribution of this concentration in a spatio-temporal context. On the other hand, the notion of accessibility as determined by the spatial distribution of potential destinations and the easiness of reaching those destinations (Church & Marston 2003) could potentially be used as a way to explain this distribution. Following from this, the aim of this study is to explore disabled peoples mobility patterns using such data.

2. Data

2.1 Oyster card

Transport for London's (TfL) own automated fare collection system uses RF-ID stamped cards (called Oyster cards) as a unified transportation ticketing system for many public means of travel.

Oyster card records with a disabled pass attribute were used to represent disabled people while keeping the total amount of passengers as exposure for the London Croydon borough. However, Oyster bus data provide boarding information only. To be consistent with this fact and avoid double counting, it was decided to use only the first validation in the case of rail and tube. The resulting observations are representing aggregated counts at each areal unit of people's location at the moment of Oyster validation. For the temporal domain, the 28th of October 2013 was used, as this was the UK peak of St. Judes' storm in London. The day was discretized in 16 approximately hourly intervals during public transport operational times excluding night buses i.e. 04:30 to 01:30 next day.

2.2 Choosing covariates

2.2.1 Accessibility covariates

This concept is closely related with the notion of accessibility of a particular area as defined by the total number of locations at which an activity can be found within a pre-specified spatial extent.

The range of possible activities was assessed with points of interest (POI) within each areal unit. OpenStreetMap (Openstreetmap.org 2014) POI database was used for this purpose. A simple categorization between the POI categories and the travel preference categories was employed using keywords appearing in the official name of the POI. The total amounts of POIs found along with the keywords used are shown in table 1:

Category	Keywords	Count
Education	School, University, Education	2006
Medical	Hospital, Health, Centre, NHS	379
Public	Library, Theatre,	58

Entertainment	Cinema	
Religious	Church, Synagogue, Mosque	1554
Shopping	Shop, Shopping Centre	1733
Social Clubs	Community, Social Centre, Social Club	701

Table 1: POI classification and counts according to categories.

2.2.1 Public Transport Accessibility Level (PTAL)

PTAL quantifies the density of public transport per area (TfL 2010). The final product is 6 levels of accessibility for every point of the extent of Greater London Area ranging from low to high (1-6).

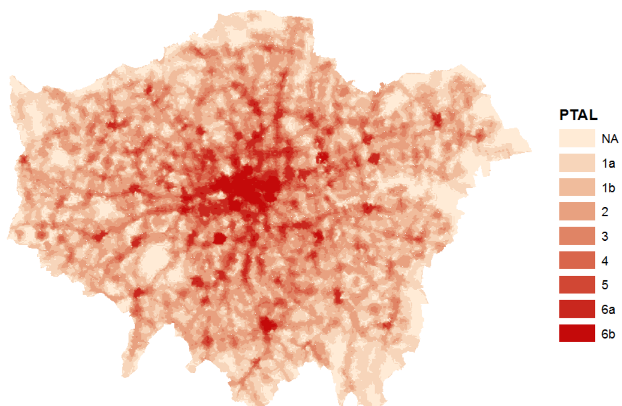


Figure 1: London PTAL levels.

3. Methods

3.1 Data preparation

The spatial domain was defined by a combination of a buffer distance around the bus stops and train stations and a Voronoi tessellation. The recommended walking distance for disabled people without a rest following (May et al. 1991) is 150m. For this research, a buffer distance of 200m was chosen to encourage the creation of a spatially contiguous area, as far as this is possible.

3.2 Defining the spatial neighbourhood

Assuming that people with disabilities will be using the bus stops located within a close proximity of their residence, it is reasonable to assume that there will be a diffusion of Oyster card observations between these stops/stations. To achieve this the following criterion was used: If two or more areas overlap, they are assumed to form a cluster. This cluster defines the most probable bus stops likely to be used by a disabled passenger residing in the proximity of each of these areas (fig 2).

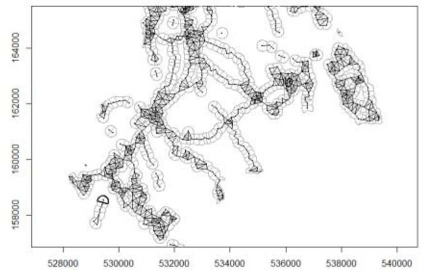


Figure 2: Neighbourhood structure (detail from Croydon borough).

3.3 Modelling

The modelling was done using Poisson spatio-temporal generalised linear models built within a Bayesian hierarchical modelling framework, ranging from simple to more complex ones, while taking into account the spatio-temporal interactions that emerge between the space-time units. The final model was:

$$Y_{it}|\lambda_{it} \sim Poi(\lambda_{it}), \qquad (1)$$
$$\log(\lambda_{it}) = \log(E_i) + \beta_0 + \beta'_i x_i + u_i + v_i + \delta_t + \psi_{it},$$

where:

Variables	Explanation
Y_{it}	Disabled users counts
λ_{it}	rate of arrival at each areal unit/time slice
E_i	the expected number of people arriving at each areal unit defined as $E_i = \frac{\sum_{i=1}^{n} Y_i}{\sum_{i=1}^{n} P_i} P_i$ where P_i is taken to be the total number of passengers in each areal unit
$\beta_{1\ldots p}$	the regression coefficients
β_0	the intercept term
u_i	the random effect
x_i	the covariates
v_i	the spatial effect
δ_t	the temporal effect
ψ_{it}	the spatio-temporal interaction term

Table 2: Model's terms.

The regression coefficients and random errors $\beta_{1\ldots p} \sim N(0, \tau_\beta), u_i \sim N(0, \tau_u)$ are assumed to be 0 centered normally distributed with precisions $\tau_u \sim Ga(a, b)$ with $a = b = 0.001$ and $\tau_\beta = 10^{-6}$. An unbounded uniform distribution prior was placed on the intercept term $\beta_0 \sim U(+\infty, -\infty)$.

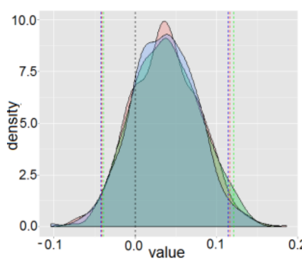
A Conditional Autoregressive (CAR) prior (Besag et al. 1995) was placed for the spatial effects v_i while two alternative priors were placed for the temporal effects: an unstructured $\delta_t \sim N(0, \tau_\delta)$, for $t = 1 \ldots T$ and a random walk prior (RW) to reflect the notion that the temporal effect is correlated with its adjacent time units with precision in both cases $\tau_\delta \sim U(0, 1000)$.

Following the framework introduced by Knorr-Held (1999) the interaction effects were assumed to have no structure in space and time so that any random deviations from the global space time trends can be revealed, providing evidence on the presence of a more complicated spatio-temporal structure.

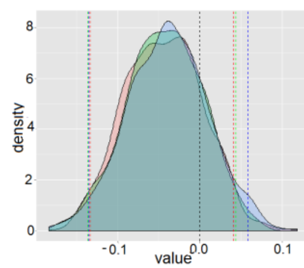
The performance of the resulting models in terms of their ability to explain the effects of the covariates as well as predicting future disabled peoples counts were compared relative to each other using the deviance information criterion and posterior (DIC) (Spiegelhalter et al. 2002) and predictive posterior loss (PPL) criterion with mean squared predictive error loss function. Inference was done using MCMC methods.

4. Results

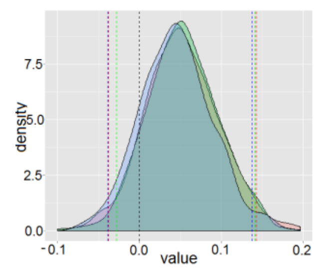
In all models, with the exception of PTAL, the effect of covariates was found statistically non-significant given that 0 value was within the 95% credible intervals (fig 3).



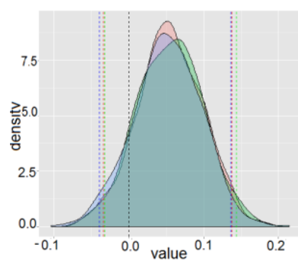
(a) Public Entertainment



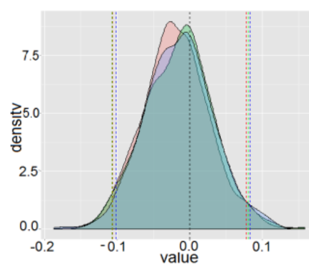
(b) Religious



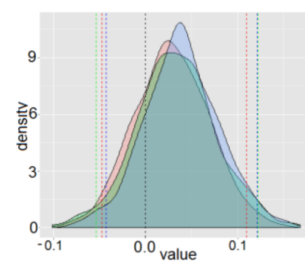
(c) Shopping



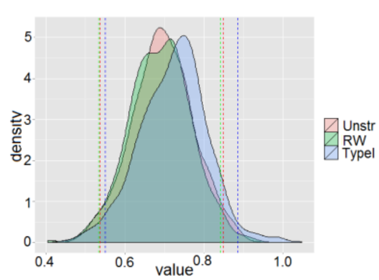
(d) Education



(e) Medical



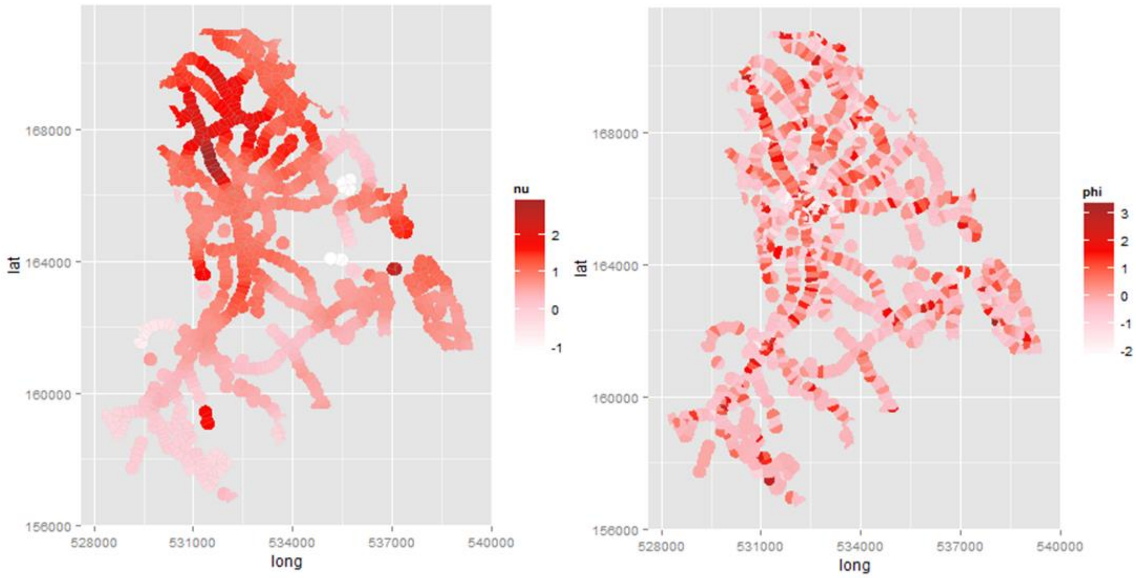
(f) Social Clubs



(g) PTAL

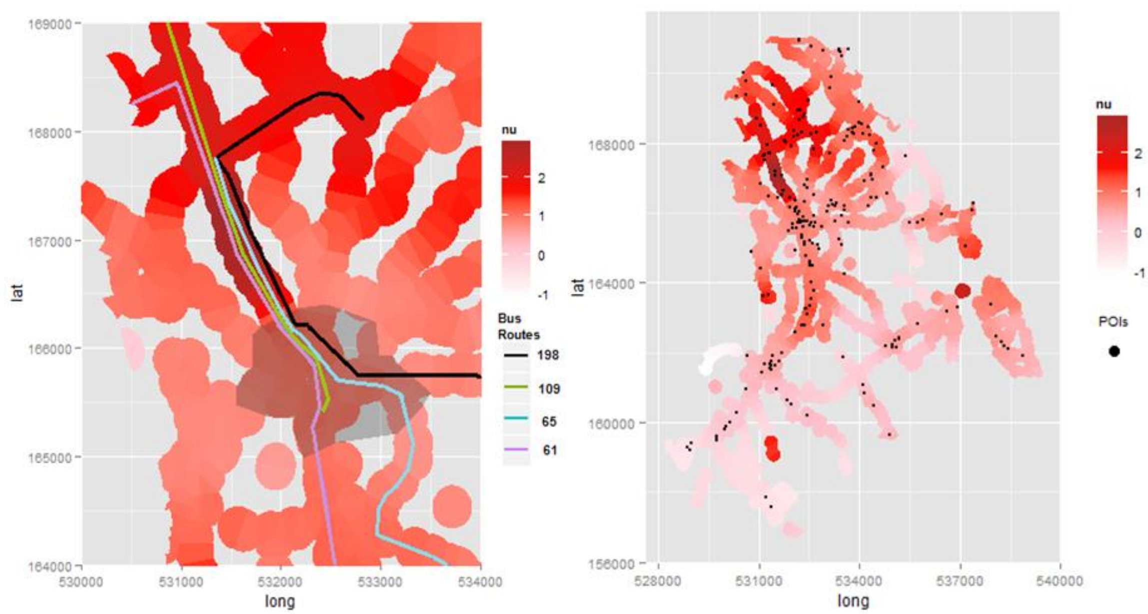
Figure 3: Posterior densities of the covariates for the spatio-temporal Oyster card data

Looking at the spatially structured effect in fig. 4 below, there is a statistically significant variability between the areal units, clustered in the north of the borough particularly where 4 bus routes overlap (fig. 5a). Interestingly, the spatial concentration of disabled Oyster card users doesn't seem to be intense in Croydon's city centre. This could explain the reduced effect of the accessibility covariates as many of the POIs are located in the city centre (fig. 5b) and could be attributed to the fact that rail services were experiencing disruptions due to the storm, as well as the overall tendency of disabled people to avoid rail travel (TfL 2012).



(a) Spatially structured effect (b) Random effect

Figure 4: Posterior means of structured and unstructured spatial effect.



(a) Bus routes and Croydon city centre (transparent black polygon) (b) Location of POIs

Figure 5: Bus routes, Croydon city centre and POI locations.

On the temporal aspect of the analysis, the lack of any time related covariates led to the manifestation of a strong temporal pattern away from commuting to and from work rush hours (fig. 6). This suggests for further research on linking the observations with sociological covariates such as unemployment, poverty, but also personal characteristics such as age.

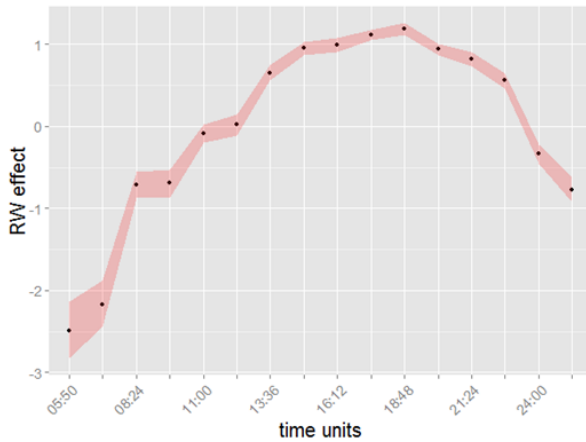


Figure 6: Posterior means and 95% credible intervals for the temporal effects.

Using the autocorrelation function of the first lag for the interaction terms, the results provided evidence to support the notion of absence of any specific structure between the spatial and temporal component of the models for the bulk of the areal units. Although the autocorrelations of the interaction effects were found to be high (most probably due to the small number of temporal slices), nevertheless for the bulk of the areal units were statistically non-significant. As it can be seen (fig. 7), there is little evidence of a strong temporal (positive autocorrelation) or spatial interdependence (spatial clustering). Hence, the interaction term acts as a white-noise "pool" capturing any residual variation.

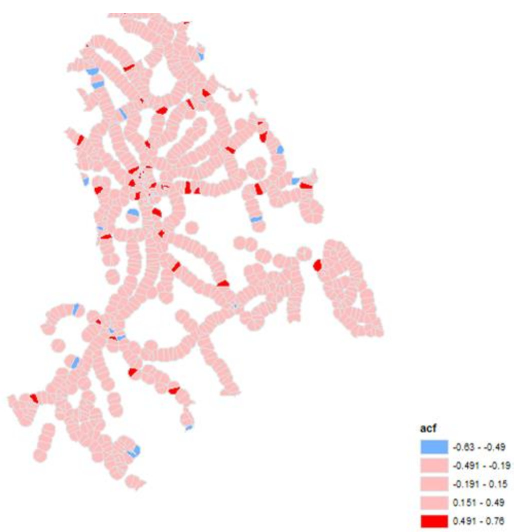


Figure 7: ψ_{it} interactions autocorrelation at lag 1. 95% confidence interval for the spatio-temporal autocorrelations was found to be +/- 0.49.

Finally, in terms of model comparison criteria, the model with the interaction term seem to outperform the other candidates:

Model	DIC	PPL (MSPE)
Unstructured δ	17845	1.2076
RW δ	17851	1.2081
Interactions ψ_{it}	16384	0.81

Table 3: Model comparison criteria for all Oyster card models

5. Conclusions

Different models were constructed in an attempt to explore disabled people's mobility patterns building up from simple to more complex models. The results of the analysis showed that identifying people with a disability for emergency response purposes can be approached from a dynamic spatio-temporal perspective. On the topic of explaining these patterns there is a need for a more thorough approach on the choice of covariates. One major drawback of the methodology is the time consuming aspect of the inferences which makes the process feasible only on strategic level, as well as the identifiability issues arising from model over-parametrisation.

6. References

Besag, J., Green, P., Higdon, D., & Mengersen, K. (1995). Bayesian computation and stochastic systems. *Statistical science*, 3-41.

Church, R. L., & Cova, T. J. (2000). Mapping evacuation risk on transportation networks using a spatial optimization model. *Transportation Research Part C: Emerging Technologies*, *8*(1), 321-336.

Church, R. L., & Marston, J. R. (2003). Measuring accessibility for people with a disability. *Geographical Analysis*, *35*(1), 83-96.

HMGovernment (2008). Identifying people who are vulnerable in a crisis: guidance for emergency planners and responders. Online; Accessed 01/06/2014.
URL: *http://www.gov.uk/government/uploads/system/uploads*

Kailes, J. I., & Enders, A. (2007). Moving beyond “special needs” A function-based framework for emergency management and planning. *Journal of Disability Policy Studies*, *17*(4), 230-237.

Knorr-Held, L. (1999). Bayesian modelling of inseparable space-time variation in disease risk.

May, A. D., Leake, G. R., & Berrett, B. (1991). Provision for disabled people in pedestrian areas. *HIGHWAYS & TRANSPORTATION*, *38*(1).

McGuire, L. C., Ford, E. S., & Okoro, C. A. (2007). Natural disasters and older US adults with disabilities: implications for evacuation. *Disasters, 31*(1), 49-56.

Metz, W. C., Hewett, P. L., Muzzarelli, J., & Tanzman, E. (2002). Identifying special-needs households that need assistance for emergency planning. *International Journal of Mass Emergencies and Disasters, 20*(2), 255-281.

Norwood (2011). Promising practices for evacuating people with disabilities. Online; Accessed 10/08/2014.
URL: *http://www.ohsu.edu/xd/research/centers-institutes/institute-on-development-and-disability/public-health-programs/upload/Promising-Practices-final-1-21-2011.pdf*

Openstreetmap.org (2014). Openstreetmap. Online; Accessed 05/07/2014.
URL: *http://www.openstreetmap.org/*

Rooney, C., & White, G. W. (2007). Consumer Perspective Narrative Analysis of a Disaster Preparedness and Emergency Response Survey From Persons With Mobility Impairments. *Journal of Disability Policy Studies*, *17*(4), 206-215.

Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Van Der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *64*(4), 583-639.

TfL (2010). Measuring public transport accessibility levels: PTALS summary. Online; Accessed 16/09/2014.
URL: *http://data.london.gov.uk/documents/PTAL-methodology.pdf*

TfL (2012). Understanding the travel needs of London's diverse communities: Disabled People. Online; Accessed: 01/08/2014.
URL: *https://www.tfl.gov.uk/cdn/static/cms/documents/understanding-the-travel-needs-of-london-diverse-communities.pdf*

Twigg, J., Kett, M., Bottomley, H., Tan, L. T., & Nasreddin, H. (2011). Disability and public shelter in emergencies. *Environmental Hazards*, *10*(3-4), 248-261.