Optimising Location under Scenarios of Changing Demand: Multi-temporal location allocation analysis

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1. Introduction

Finding optimal location for service facilities for a spatially distributed demand is important in the field of location planning. To address this problem, numerous location models have been suggested. These include the *P*-median model (Hakimi, 1964), Maximal Covering Location Problem (Church and ReVelle, 1974) and Set Covering Models (Torges et al, 1971).Example application includes:optimization of mobile health facilities such as blood banks (e.g. Jacobs et al., 1996; Eaton *et al*.,1986; Price and Turcotte, 1986); finding suitable locations for emergency service systems such as fire stations (Schreuder, 1981; Badri *et al.*,1998; Serra and Marianov, 1998) to ensure fast response during fire emergency; location of public facilities such as post-offices (Comber *et al*, 2009); libraries (Koontz et al., 2009; Park, 2011); schools (Pizzolato and Silva, 1997). In all of these case studies, demand has been treated as static or stationary over time. Using static assumptions about demand could affect accuracy and effectiveness of location decisions, there by resulting in sub-optimal location choices. Few studies have employed dynamic strategies to location planning by the application of time series analysis. For example, Kumar (2004) investigated changes in geographical access to public and private health services India, using 2-year census (1981 & 1991) estimates. Similarly, Bennett (1981) compared alternative scenarios to locating health services by using a 2-year projected population.

This paper proposes a method for developing location solutions in conditions when demand changes. Identifying future locations for service facilities may be considered as a spatial trajectory problem whose location or path depends on a sequence of past events. Drawing ideas from data mining literatures (eg: Brakatsoulas*et al.*, 2005; Laube and Purves, 2011) this research develops a method for optimising locations for outreach clinics using mortality data describing death due to respiratory diseases. The study compares outcomes from using traditional static 'non-trend weighted location models' from those derived by the application of dynamic 'trend-weighted location allocation approach'. In the context of this study, a 'trend-weighted location model' is described as a method that extracts temporal or dynamic information from the dataset by the application of time series analysis. This differs from a static 'non-trend weighted approach' that gives equal weights to data points in the series. The aim is to apply a predictive location allocation strategy to help identify suitable locations for outreach clinics in Leicester city.

2. Method

2.1 Data Processing

In order to demonstrate the effect of temporal trends on location allocation decisions, this study uses data covering a ten-year period (2001 – 2010) of mortality due respiratory diseases. Mortality locations were based on postcodes and classified according to the International Classification of Diseases (IDC). Figures 1, displays small map multiples of spatio-temporal trends of mortality in the study area. As can be seen from Figure 1, the pattern of mortality from respiratory diseases varies spatio-temporally over time. This variation needs to be taken into account, when planning suitable location for outreach clinics. In order to achieve this; a double four-year moving average was applied to forecast values from previous mortality estimates. A double moving average is a moving average on a moving average (Hyndman, 2009). This procedure is applied to series with significant trend. Hence, the choice of a double moving average was due to the existence of an upward trend in mortality across the study area. Double four-year moving average was derived for individual Super Output Areas (SOAs) in the study area. This was necessary to ensure that local trends within spatial units were taken into consideration in the analysis. The values derived from the forecast were subsequently used as demand weights in the *P*-median model (see equation (1)). Non-trend weighted demand applied, in this study was derived by simply finding average values of mortality estimates in each SOA in the study area.

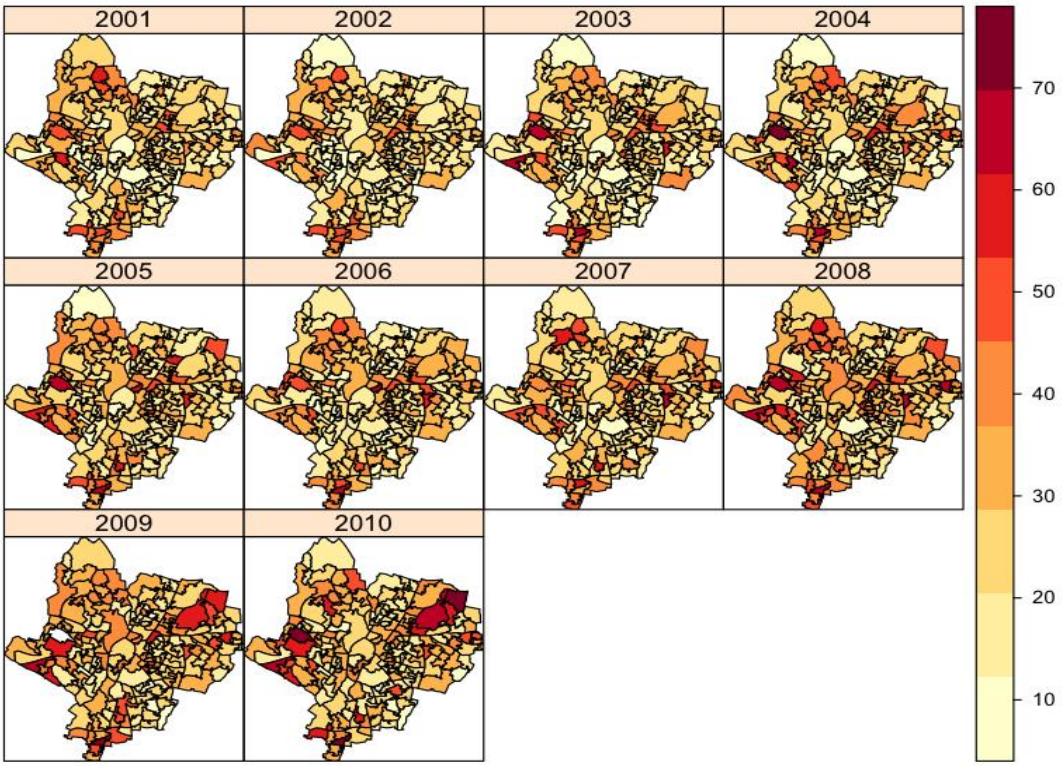

Figure 1. Spatio-temporal trend in mortality from respiratory diseases in Leicester City (2001 – 2010)

2.2 Problemformulation and model parameters

Location model used in this study was the *P*-median model. *P*-median selects a subset of facilities known as '*P* facilities from a given set of candidate facilities that minimizes the aggregate travel time or distance between demand and nearest facility locations (Fotheringham *et al.*, 1995). In this study, the classical *P*-median model first espoused by ReVelle and Swain (1970) was modified to account for trend by incorporating forecasted values as demand weights in to *P*-median model.

$$\text{minimise} \sum_{i=1}^{m} \sum_{j=1}^{n} a_i d_{ij} x_{ij} \qquad (1)$$

Based on equation (1), the following parameters are defined.
P = Number of optimal outreach points to locate (7locations).
I...m = set of demand locations (187 centroids of SOAs in Leicester city)
j...*n* = set of candidate locations for outreach clinics (734)
a_i = Weight at demand nodes (population in each SOA weighted by trend or non-trend weight of each SOA)
d_{ij}= Denotes the shortest distance between point *I* and *j* derived for GIS network analysis
X_{ij}= Decision variable with values [0, 1] to showsites selected.

Typically, location allocation problem involves selecting optimum location choices from a set of candidate locations and allocating demands to these points. The pool of candidate location consists of 734 simulated points in the study area; with a choice of selecting 7 optimal outreach locations to allocate demands in 187 SOAs in Leicester. Finding solution for this type of problem is computationally difficult. For example, choosing a subset of 7 optimal locations from a set of 734 locations requires the application of a solution search space of 734! / 7! * (734 – 7)! .Due to this intractability, the modified *P*-median problem was solved using a modified Grouping Genetic Algorithm (GGA). This was based on a stopping criterion of 20000 iterations. The GGA was developed by Comber *et al* (2011) to handle subset selection location problems. GGA has been successfully implemented on location optimization problems (e.g. Sasaki *et al.*, 2010 and Comber *et al.*, 2009).

3. Discussion and Initial results

Figure 2 shows distribution of optimal outreach clinics derived from the application of the *P*-median model given in equation (1). This shows the best spatial arrangement for outreach clinic locations to ensure effective intervention. As can be seen in the Figure 1, different set of optimal locations were selected for trend and non-trend weighted methods. This suggests that applying a non-trend weighted approach would affect location allocation results.

Table 1, summarisesthe difference in the proportion of demand allocated to each optimal outreach clinic based on trend and non-trend methods. The unique ID of selected locations is denoted as P. As can be seen from the table, the proportion of demands allocated to each outreach location is different between trend and non-trend weighted approach. The

differences suggest that not accounting for temporal trends in demand data could result to misallocation of health resources. For instance, in trend-weighted approach, the largest proportion of demand (23.96 %) was allocated to location {275}. This differs from non-trend methods, where though same location was selected, but with different proportion, of demand allocated it (25.5%). In addition, some similarities exist in demand allocation schemes using the two methods. For example, locations {260,270, 323,349, and 275} have same percentage of demands allocated to them. This indicates the similarity in the spatial distribution of selected locations between trend and non-trend weighted approach. Furthermore, it is also possible that the change in mortality in these areas is not sufficient to trigger selection of other sites.

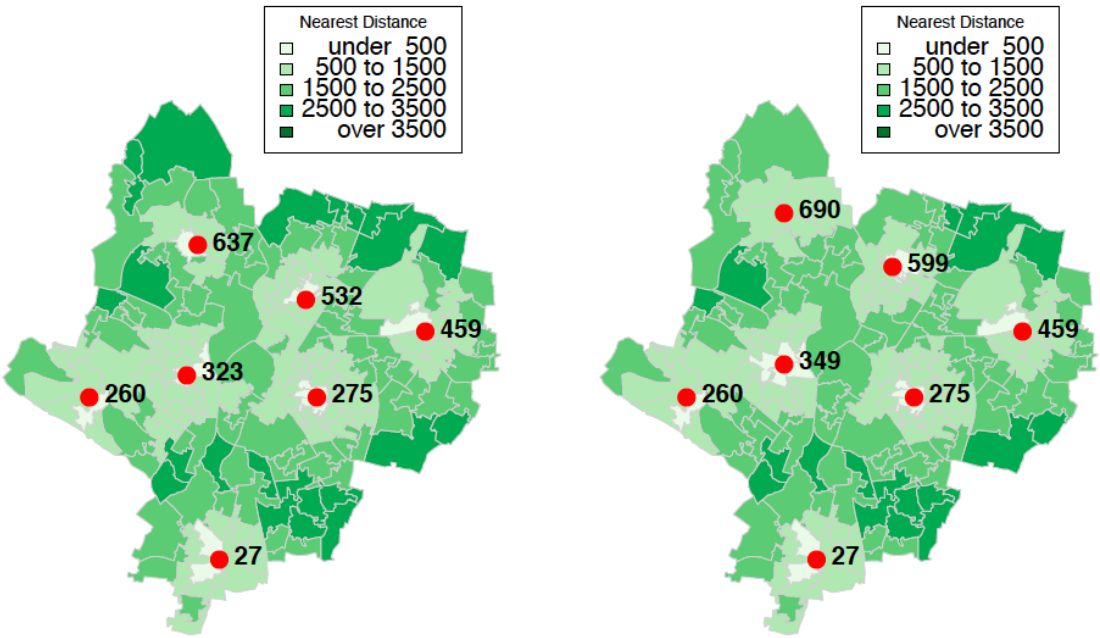

Figure 2 Optimal Locations of Outreach Clinics based on Trend (*left*) and Non-trendWeighted (*Right*).

Table 1: Summary of Differences in demand allocation for trend and non-trend weighted distance

Trend Weighted			**Non Trend Weighted**
P	Demand Allocation (%)	*P*	Demand Allocation (%)
260	20868 (7.45)	260	20868 (7.45)
27	37838(13.51)	27	37838 (13.51)
323	47343(16.91)	349	47325(16.91)
459	37822(13.51)	459	39254 (14.02)
532	42803(15.29)	599	43018 (15.37)
637	26171 (9.34)	690	20228 (7.22)
275	**67076 (23.96)**	275	**71390 (25.50)**

Further exploration of the differences by varying the number of optimal sites (*P*) shows that the observed differences remains despite increasing or reducing the number of optimal locations to be sited (see Figure 3). In addition, the graph indicates that average weighted distance values for trend weighted is significantly higher compared to non-trend weighted

distance. This suggests that using non-trend approach will underestimate the distance to optimal outreach locations and could have effect on spatial planning of outreach locations.

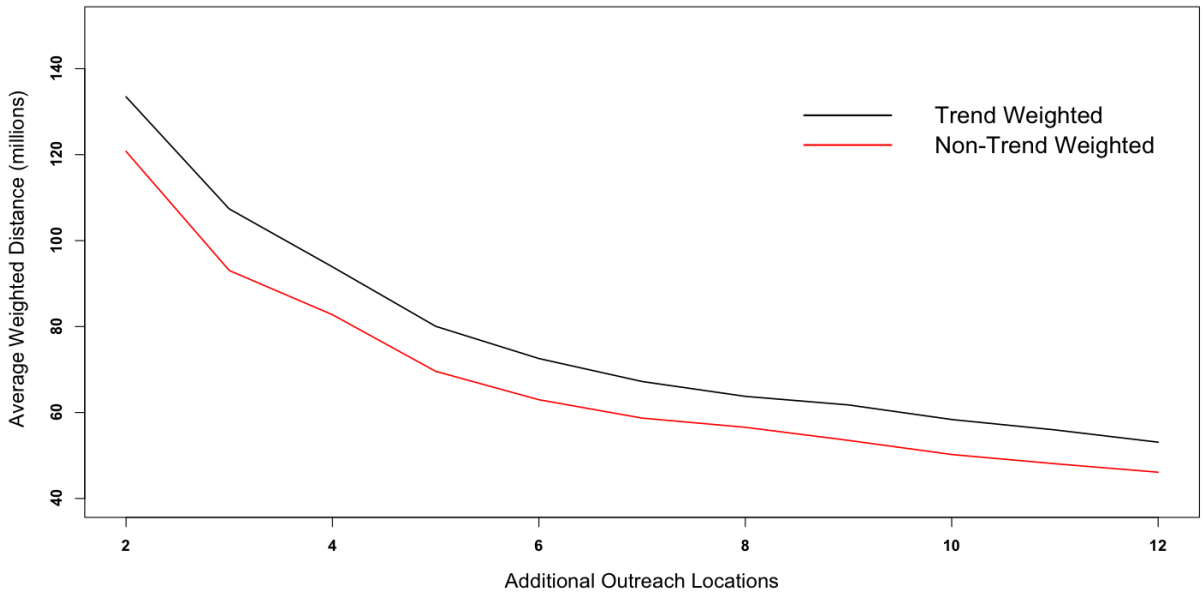

Figure 3.Relationship between average weighted distance and additional outreach Locations

4. Conclusion

This research highlights the need to incorporate dynamic methods in location planning. Overall, the result from the comparison of trend and non-trend weighted location model shows that not exploiting sufficient temporal information from demand data leads to different location and allocation decisions. This is because different set of location were selected from the application of trend and non-trend weighted approach. In order to forecast locations for mobile outreach clinics, an understanding of the pattern and direction of trend is important. This will enable decision markers and location analyst to predict accurately the location of target audience or at-risk population and identify suitable locations to position mobile outreach. Approaches that do not exploit trend, could result to loss of information regarding at-risk or target population.

5. References

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6. Biographies

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