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Network Accuracy: the impact of the 3D distances on location-allocation

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Abstract

Distance metrics derived from road networks are used in location-allocation models to support facility planning. Typically, road networks model 2-dimensional distance (i.e. over X and Y dimensions). This paper introduces the notion of '3D distance' that incorporates elevation as the Z-dimension in the network. A comparison of distance modelled in 3D networks with that in 2D networks demonstrates the impact of 3D distance with that each distance type resulting in different sets of optimal locations given same P-median problem.

Keywords: Location-allocation, P-median, networks

1. Introduction

Location-allocation models seek to select an optimal set of locations given a set of supply and demand locations, evaluated over some criteria – typically minimising a measure such as *demand weighted distance*. Thus distance is an important component of location models. The quality of the distance information has a considerable impact on the quality of the solutions (Krarup and Pruzan, 1980) as the accuracy of the outcomes depends on how distance between facility location and demand is specified. A review of the literature shows that previous work in this area apply only 2D distance metrics to address location problems such as network distance (with and without travel time) and Euclidean distance. For example Schuurman et al., (2006), used network distance with travel time to model rural hospital catchments areas in British Columbia, Sinuany-Stern et al (1995) used Euclidean distance to identify suitable location for a hospital. Other work has combined two metrics to produce hybrid location models. For example, Møller-Jensen, and Kofie (1998) proposed a model that combined network and Euclidean distances to locate health services in Ghana. However, the problem with 2D distance metrics is that they ignore the effect of elevation, which will in turn affect location decisions. Alternatively, the concept of *3D Distance* recognises the impact of elevation on distances and travel times in transport networks.

This study compares the impact of 2D and 3D networks on location-allocation decisions and by accounting for elevation in 3D distance networks, seeks to provide a more robust and intuitive approach to modelling supply in relation to demand.

2. Methods

2.1. Study Area

The study area is South Yorkshire in the UK. It contains 845 census areas (Lower Super Output Areas - LSOAs) with a mean population of approximately 1500 people (ONS, 2005). The city of Sheffield is located at the West of the study area has the highest population and is bordered to the West with hilly terrain – the Pennines. The variations in elevation follow a west-east orientation (Figure 2), with the highest peak at the western border of the region.

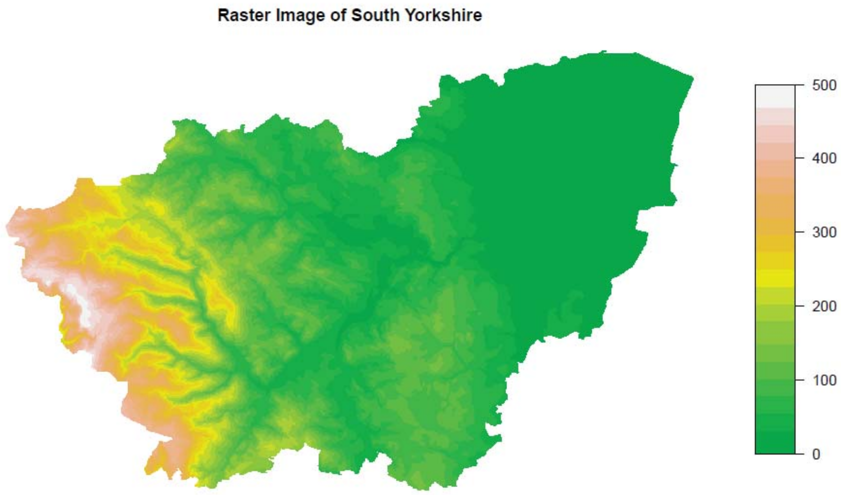


Figure 1: Elevation in the study area.

2.2. Study Area and Data

Location optimisation identifies the best set of locations, given some spatial distribution of demand. In location-allocation models optimally is typically determined over distances between sets of demands locations and supply locations. Distances between demand and supply points could be along a straight line as in the case of Euclidean distance or along road, (e.g. network distances and travel times). In this study, 845 demand points were derived from centroids of the LSOA census areas and the amount of demand at each location was the total population in the census area, as recorded in the 2001 census. Supply points representing potential locations for say EMS or ambulances were determined using regular 500m grid points, selecting those within 50m from existing roads. In total 3038 potential supply locations were identified. Road data was derived from Ordnance Survey Meridian data and included different classes of roads. Ordnance Survey 10m elevation data was used to extract z-values for road nodes and edges and a GIS-based network analysis was used to calculate 2D and 3D distances between demand and supply points. Distance estimates from network analyses were used as input into the P-median model to find optimal locations for EMS. In this study, 3D travel time was derived by extracting elevation (z values) of road nodes and arcs from a digital elevation model of the study area. Travel time values were estimated from speed limits of roads types and length of road arcs, weighted by z values from elevation data. The 3D travel time distance between two points (x_1,y_1,z_1) and (x_2,y_2,z_2), connected by a straight-line can be estimated as:

$$3D\ Distance = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \qquad (1)$$

where z_1 and z_2 represent the minimum and maximum height value for start and end nodes of the line. Elevation values for road nodes and edges were interpolated from a mosaicked raster image of the study area. The resultant network was used to analyse the shortest distance between set of potential EMS sites (supply points) and demand locations.

2.3. P-median model

The location-allocation model used in this study was the P-median model. It selects a subset of facilities from a given set of candidate facilities that minimises the aggregate travel time or distance between demand and nearest facility locations (Fotheringham, et al., 1995). In this study, the classical P-median model was modified to account for 3D distance by adding a z dimension to demonstrate the effect of elevation as shown in equation.

$$minimise \sum_{i=1}^{n}\sum_{j=1}^{m} a_{i_{t_n}} * d_{ij(Z)} * x_{ij} \qquad (2)$$

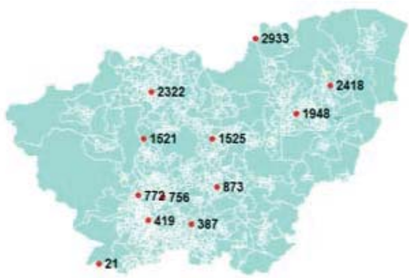
where *i...n* is set of demand locations (845 centroids points weighted by night and day time population), *j...m* is a set of candidate EMS locations (3038 EMS potential locations), $a_{tn =}$ are demand weights (population), d_{ijz} denotes the shortest distance between point *i* and *j* , based on various distance types, and x_{ij} is the decision variable with values [0, 1] to show which sites where selected.

In this study optimal sites are those locations that minimise the weighted distance between demand (LSOAs) and supply points (EMS). Location-allocation problems involve selecting the optimum *n* locations from a pool of *N* candidate location and allocating demands to these points – in this case the 3038 simulated points in the study area.

The objective was to select the 12 optimal locations based on the populations in 845 census areas. Identifying the solution for this type of problem deterministically is computationally demanding - a subset of 12 locations from a set of 3038 locations requires a solution search space of 3038! /12!*(3038-12)! Due to this dimensionality the P-median problem was solved using a modified Group Genetic Algorithm (GGA) developed by Comber et al. (2011) which has been has been successfully tested on a number of location-allocation problems (e.g., Sasaki et al., 2010 and Comber et al., 2009).

3. Results

The results of applying the P-median model (2) using 2D and 3D distances select different sets of locations (Figure 2) and that different distance metrics have an impact on optimal locations and planning decisions. Table 1 shows the selected sites the demand allocated to each site under the different distance metrics. The implication of this outcome is that different demand with distance metric influences EMS location planning decisions. However, it is important to note that 3D travel time distance is a more realistic approach to quantify distance between potential facility locations and demand.



2D 3D

Figure 2: Distribution of optimal locations for using different metrics of distance

Figure 2 shows the spatial distribution of selected optimal sites based on different metrics of distance. The difference in these locational decisions may be critical for example to EMS response times if the spatial arrangement is not optimal. Each site has a proportion of the total demand allocated to it (Table 1). This suggests that location decisions are affected by different distance metrics.

Table 1: Optimal locations and allocations using different distance metrics.

2D Distance		***3D Distance***	
Site	*Catchment*	*Site*	*Catchment*
2007	183062 (14.45%)	21	225952 (17.84%)
402	166809 (13.17%)	419	134754 (10.64%)
225	149663 (11.81%)	2933	134067 (10.58%)
2411	129800 (10.24%)	1948	127315 (10.05%)
1803	113853 (8.99%)	873	110932 (8.75%)
1024	108026 (8.53%)	1525	105304 (8.31%)
756	88004 (6.94%)	2322	86625 (6.84%)
772	82476 (6.51%)	756	84768 (6.69%)
1521	76356 (6.02%)	772	78073 (6.16%)
914	60864 (4.80%)	1521	64561 (5.09%)
2615	54902 (4.33%)	387	61005 (4.81%)
278	52533 (4.14%)	2418	52992 (4.18%)

3. Conclusions

This initial analysis shows that different distance types have considerable impacts on the locations that are selected in a standard location-allocation (supply and demand) due to the different sets of locations selected under different distance measures. The implication of this research are that decision of where to site particular facilities (e.g. EMS or ambulances) especially in relation to response times may be inappropriate as the evaluation may under-estimate or over-estimate the impacts of distance. 3D distances offer a more realistic calibration of distance between facility and demand as compared to planar based or 2D metrics. The results of this analysis show that location decision for EMS is sensitive to the metrics of distance used to analyse a location problem. Many studies on location-allocation to date have only applied 2D distance metrics to location problems. This study introduced a new distance metric for location models.

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