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Spatio-temporal Analysis of Noise Pollution near Boston Logan Airport: Who Carries the Cost?

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Abstract

Airports are often located near densely populated residential areas, affecting a large number of people. Thus, knowing socio-demographic characteristics of the noise-affected areas is important for the development of policies on noise control and abatement. This study proposes a new methodology that combines airport noise models with spatial statistics and geographical information systems to identify spatial clusters of socio-demographic characteristics in relationship to the noise level. Statistically significant 'hot' and 'cold' socio-demographic clusters represent spatial concentrations of certain social groups, corresponding to various levels of vulnerability to environmental impacts. Results show that the population 'paying' for the cost of noise from Logan International Airport in Boston, USA, is highly vulnerable as there are more minority and lower-income populations, and lower house prices in the noise-affected areas. These results should draw the attention of policy-makers and the public as policies for noise abatement are being developed.

1. Introduction

Excessive noise from airplanes negatively affects human health and can contribute to loss of hearing, sleep disturbance, hypertension and cardiovascular problems. Airplane noise is more annoying to humans than train noise, even if the noise level is the same (Miedema, 1992). Some studies also link elevated noise level with reduced academic performance (Evans and Maxwell, 1997; Haines *et al.*, 2001; Stansfeld *et al.*, 2005). Current regulations state that residences, schools, hospitals and churches are considered

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incompatible with a noise level over 65 dB and they can only be compatible with this noise level if they are sound-insulated (Massport, 2006). It is important to know the socio-demographic composition of the vulnerable population living in the noise-affected areas in order to develop effective policies on noise control and abatement.

This study proposes a new methodology that combines computer technologies such as airport noise modelling and geographical information systems (GIS) with techniques of spatial statistics to identify spatial clustering of several socio-demographic characteristics in relationship to the noise level near Logan International Airport in Boston, Massachusetts. The two research questions addressed in this paper are

(1) Does the cost of noise from the airport fall disproportionately on minority and low-income populations?
(2) Were there any changes in the socio-demographics of the affected area between 1990 and 2000?

Answering these questions is important because: it allows for assessment of the vulnerability level of the noise-affected population; it provides statistically grounded and easy-to-interpret visual results that could support policy-makers in their decision-making process regarding noise abatement; and the proposed novel methodology can be applied to other noise-affected areas for comparative analysis and policy applications.

Boston's Logan airport is New England's primary international and domestic airport and was the 17th-busiest commercial aviation facility in the US in 2007, ranked by aircraft operations (US Federal Aviation Administration, 2007). Unlike many other airports, it is located close to the city centre and is surrounded by densely populated residential areas with a high percentage of low-income and minority inhabitants. According to the most recent Environmental Data Report issued by Massport, 5583 people (about 1 per cent of the entire population of the noise-affected towns) resided in the areas exposed to noise levels higher than >65 dB (Massport, 2006). It is for these reasons that Logan Airport was chosen for this case study.

Several studies have explored the relationship between noise pollution, race/ethnicity, low-income level and housing sale price. Many studies on the environmental impact of noise have used GIS, as it provides tools for spatial database development, spatial analysis and visualisation (Kluijvera and Stoterb, 2003). Forkenbrock and Schweitzer (1999) studied noise pollution as one of the many environmental justice issues that are raised by transport systems. The researchers were interested in the air and noise pollution effects of a major US highway that runs through the centre of Waterloo, Iowa. This study used a computer noise propagation model derived from the Federal Highway Administration's STAMINA model to create noise contours for the maximum estimated noise levels that can be projected in a GIS. These contours were displayed with census-block data for income and race. The study expected to find minority and low-income populations disproportionately represented in the areas of noise pollution. The hypothesis proved true for the minority group, but not for the low-income group.

A study conducted by economists in 1985 attempted to answer questions about the relationship between airport noise and residential property values, using US census-block data and individual house sales data (O'Byrne *et al.*, 1985). The study used a noise contour map with 5 dB day–night average sound level (DNL) increments for the area around the Atlanta International Airport. Using address data for each of the house sales, the researchers were able to assign a DNL value for each property sale location. These values were analysed along with sale value data from both the individual sales data and from the Census property value estimations. The study found that, for each decibel of noise, the house value was discounted a mean of 0.62 per cent. Ten other studies, conducted for the years 1967–76, all found a significant discount in housing prices due to high noise levels, ranging from 0.40 per cent to 1.10 per cent (O'Byrne *et al.*, 1985). Several other studies have examined the effect of noise pollution on neighbourhood attributes; all the studies concluded that noise pollution had a negative and statistically significant impact on property values (Espey and Lopez, 2000; Hui *et al.*, 2006; Pennington *et al.*, 1990) and the residential housing market (Baranzini and Ramirez, 2005; Levesque, 1994; Tomkins *et al.*, 1998).

Another recent study focused on the decisions of spatial scale and target populations when conducting an environmental justice analysis and used noise pollution at St Louis-Lambert Field as a case study (Most *et al.*, 2004). Investigators used Integrated Noise Model 6.0c to produce noise pollution contours for the years 1990 and 2000. Using these contours, census block groups were clipped and the census data for 1990 and 2000 analysed. The study determined that, for the two different years, a number of different selection methods based on geographical location could be applied to the census data. As a result, the populations affected by noise pollution varied greatly, based on selection method and the following data analysis. Investigators found, however, that there were smaller percentages of low-income and minority populations living in areas with high noise levels (70–75 dB) than there were living in areas with lower noise levels (60–65 dB.) Brainard *et al.* (2004) in their study of noise pollution in Birmingham, UK, concluded that the association between noise exposure and ethnicity or socioeconomic deprivation is weak.

Our study contributes to the on-going discussion on inequities in noise exposure between different population groups by proposing a new analytical framework which combines well-known methods of spatial analysis (spatial overlay and aerial interpolation) with recently developed GIS-based techniques of cluster analysis. The conventional way of integrating GIS tools into environmental impact assessment is to use spatial overlays to identify areas of negative impact and calculate statistics (mean, range of values, etc.) for this area for the comparison with non-affected areas. We propose a new approach, based on techniques of spatial clustering. This method allows the identification of groups or clusters, of a particular phenomenon in space (often referred to as cold and hot spot analysis).This technique is grounded in statistical theory and provides confidence that clustering of similar values truly exists. Simple mapping of attribute values is very subjective and can not provide any robust measures of underlying patterns (Mitchell, 2005). Our study is the first using clustering techniques to study noise pollution.

2. Data

Two datasets were used in this study: data related to the airport operation necessary for noise-level modelling; and socio-demographic data from the US population census.

We performed our own noise-level modelling using the Integrated Noise Model (INM), version 6.0c, developed under the auspices of the FAA. We used this programme because it is an industry standard for modelling noise from airport events (arrivals and departures). Certain information such as the shape, length and spatial location of Logan Airport's runways and the noise profiles of the airplanes flown in the US was embedded in the software used for the noise modelling. Using Transtat, the Bureau of Transportation

Statistics on-line database, we tracked the number of departure events from Logan Airport in 1990 and 2000, also noting the type of aircraft (USDOT, 2005).Knowledge of the flight paths airplanes follow for each of the runways at Logan Airport is also important, as they are required input data for the noise level model. The national Aeronautical Charting Office offers data that depict the runways and how an airplane will approach and take-off from a certain runway (NACO, 2005). With this information, we drew the appropriate tracks as lines for the Logan Airport in INM. Runway usage information and the ratio of day-time flights to night-time flights for each type of airplane is another type of input required by the model. These data for Logan Airport were obtained from the most recent Environmental Data Report (Massport, 2006). The final outputs of the model are contour lines which represent noise as a day/night annual average sound level.

A noise level over 60 dB is considered the baseline level for evaluation of aviation noise impact by the Federal Interagency Committee on Noise (Most *et al.*, 2004). Due to the positional uncertainty associated with the modelled noise contours, we decided to increase the impact area to include the 55 dB contour. Noise level contours were created by INM starting with 55 dB in 5 dB increments up to 85 dB for 1990 and 2000 (Figure 1). As can be seen on these maps, the noise contours follow the shape of the runways and some of them extend as far as 21 km away from the centre of the airport. Thus, the area with a 21-km radius around Logan Airport was selected as the study area. This distance ensures that all areas affected by elevated noise and the people who reside in these areas are included in the analysis.

Census data for 1990 and 2000 were obtained from MassGIS (MassGIS, 2003) and mapped using ArcGIS software. Four sociodemographic indicators were selected for the analysis: Black and Hispanic population percentages, median household income and median house value. These particular variables

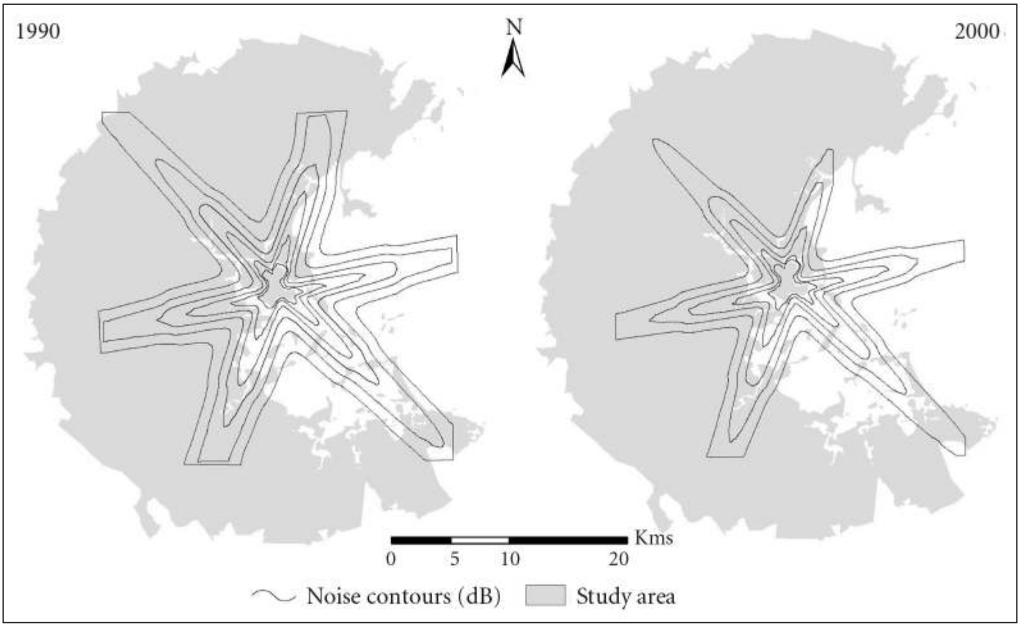

Figure 1. Noise contours for Logan Airport, 1990 and 2000. The outermost contour corresponds to 55 dB, the innermost to 80 dB

are often used in environmental equity studies and for the definition of environmental justice populations (EOEA, 2002). Careful choice of geographical unit of analysis is important in any spatial study, especially in studies of environmental inequalities, because it may affect outcome and validity (Cutter *et al.*, 1996; Most *et al.*, 2004). We chose to use the census block group as the unit of analysis because it is the smallest geographical unit for which the socio-demographic data in which we are interested are available from the US Census Bureau. The average size of the census block group in our study area is 0.2 square km. The average number of people per census block group is 1158.

3. Methods

Three types of spatio-temporal analyses were conducted in this paper. First, the noise-affected and not-affected areas were compared based on the four socio-demographic indicators from 1990 and 2000 census data. Secondly, spatial statistics methods were used to identify clusters of high or low values of these indicators to see if they coincided spatially with high noise levels. Thirdly, socio-demographic indicators were analysed for different noise ranges to identify spatial trends associated with noise level.

3.1 Identifying Noise-affected Populations

Noise contours were overlaid on census block group boundaries in GIS to select the affected area. There are various population assignment methods that can be applied using the GIS environment to define the affected area, such as within analysis, adjacency analysis and areal interpolation (Most *et al.*, 2004). We chose to test all three methods in this study. The within analysis method selects only units completely contained within the delineating boundaries of noise contours, while the adjacency analysis selects units contained both completely and partially within the delineating boundaries of noise contours. As a result, very few block groups were selected when the within analysis was used and too many block groups were selected when the adjacency analysis was used. Thus the areal interpolation method was chosen as the most appropriate.

Using areal interpolation, noise contours were intersected in GIS with census block group boundaries. As a result of this intersection, the original census block group polygons were often split by noise contour lines into several smaller polygons, each falling into different ranges of noise level. Areal interpolation was applied to calculate new population data (for example, the number of Blacks and Hispanics) for each of the new, smaller polygons. This method assigns new values to the smaller polygons according to the proportion that their areas occupy in comparison with the total area of the original polygons (Most *et al.*, 2004). This method assumes that population is uniformly distributed within the original census block group polygon. Given the high population density and urbanised character of the study area, we argue that this assumption is reasonable in this context.

The other two socioeconomic indicators, median household income and the median house value, were assumed to remain the same for the smaller polygons as for the original block group, so they did not require recalculation. Thus, the whole study area was divided into two groups: a noise-affected area, in which noise levels are greater than 55 dB; and a quiet area, which falls outside the noise contours. The four socioeconomic indicators were calculated for the noise-affected and quiet areas in 1990 and 2000 for comparative analysis (Table 1).

3.2 Socio-demographic Clustering and Noise Exposure

The spatial distribution of the four socio-demographic indicators within the whole

Table 1. Average values for noise-affected and not-noise-affected ('quiet') areas for 1990 and 2000

	Median household income ($)	*Median house value ($)*	*Percentage of Blacks*	*Percentage of Hispanics*
1990				
Quiet areas	43 320	192 222	8.1	3.6
Noise-affected areas	33 097	154 798	11.5	7.4
2000				
Quiet areas	61 570	257 425	9.1	5.7
Noise-affected areas	43 525	223 687	6.6	15.5

study area was analysed using spatial statistics techniques: global and local Moran's I coefficients. These methods identify statistically significant spatial clusters of similarly high or low values by comparing the values of each observation and its neighbours to the mean value for the entire dataset and calculating local Moran's I for each observation (Anselin, 1995; see Mitchell, 2005, for formula and detailed explanation). The 'neighbourhood' for each observation is usually defined based on the degree of spatial autocorrelation among all observations. Local Moran's I coefficient has been widely used in various applications, ranging from the identification of ethnic neighbourhoods (Logan and Zhang, 2004) and concentration of urban poverty (Orford, 2004) to disease clusters (Jacquez and Greiling, 2003) and landscape patterns (Pearson, 2002). Our study is the first in which techniques of spatial statistics are used in the context of airport noise pollution.

Local Moran's I coefficients were calculated using GeoDa software (Anselin, 2003) for each census block group for the two years for four indicators using the nearest-neighbour weights matrix, as this produced the highest values of global spatial autocorrelation index (global Moran's I). To test the statistical significance of these results, Z-scores were also calculated and mapped. Figures 2–5 show block groups which had statistically significant z-scores (at the 95 per cent confidence level) as clusters of similar high or low values.

Once identified, these clusters were then overlaid with the noise contours to see if there is some degree of spatial coincidence between certain types of cluster and the level of noise. Using this spatial overlay approach we were able to answer the following questions. Are clusters with a high percentage of Hispanics or Blacks located in the high noise area? Are clusters of low house values or low median household income also located in the high noise area? Was there a change in spatial distribution of these clusters between 1990 and 2000?

3.3 Socio-demographics within the Elevated Noise Area

The next step of the analysis focused exclusively on the elevated noise area. Once the noise-affected area was identified, we examined if and how socio-demographic indicators varied within this area as the level of noise increased. Our hypothesis was that, as the level of noise increased, the percentage of minority populations increased, while the median household income and median house value decreased.

The areas inside the 75, 80 and 85 dB contours fell mostly inside the airport boundaries and were excluded from this analysis. Therefore, four ranges of noise level were used in the analysis: 55–60, 60–65, 65–70 and

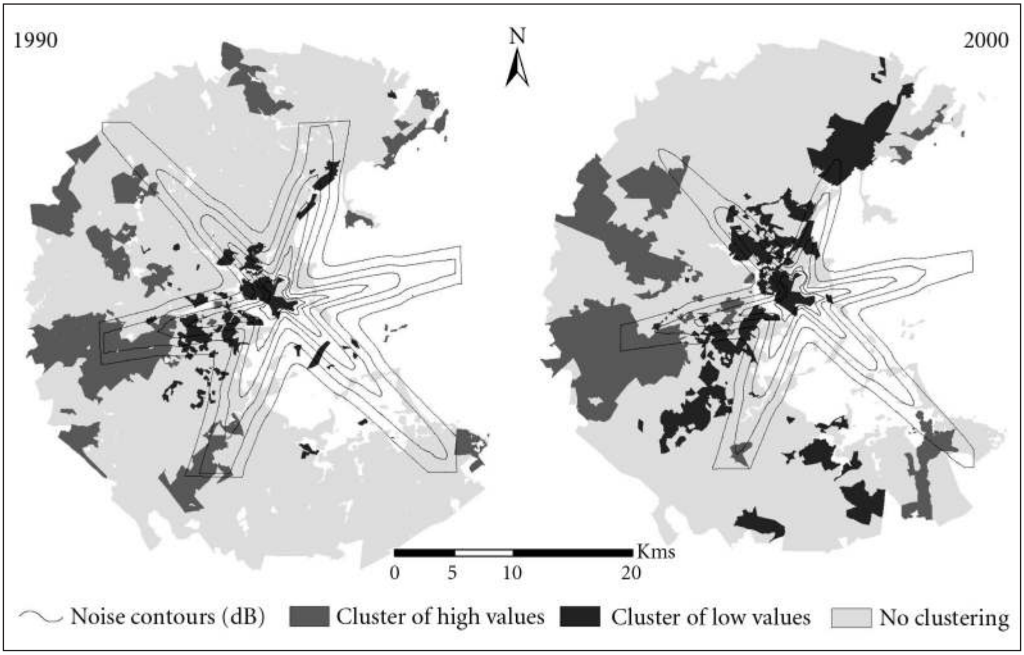

Figure 2. Spatial clusters of block groups with similar high or low median house values, 1990 and 2000 (statistically significant at the 95 per cent level)

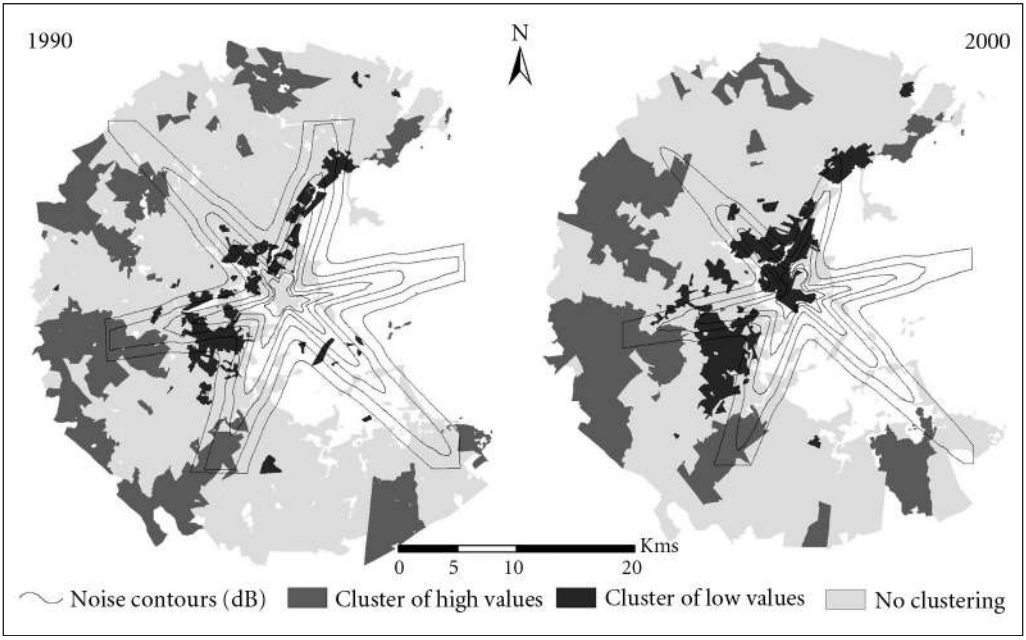

Figure 3. Spatial clusters of block groups with similar high or low median household income values, 1990 and 2000 (statistically significant at the 95 per cent level)

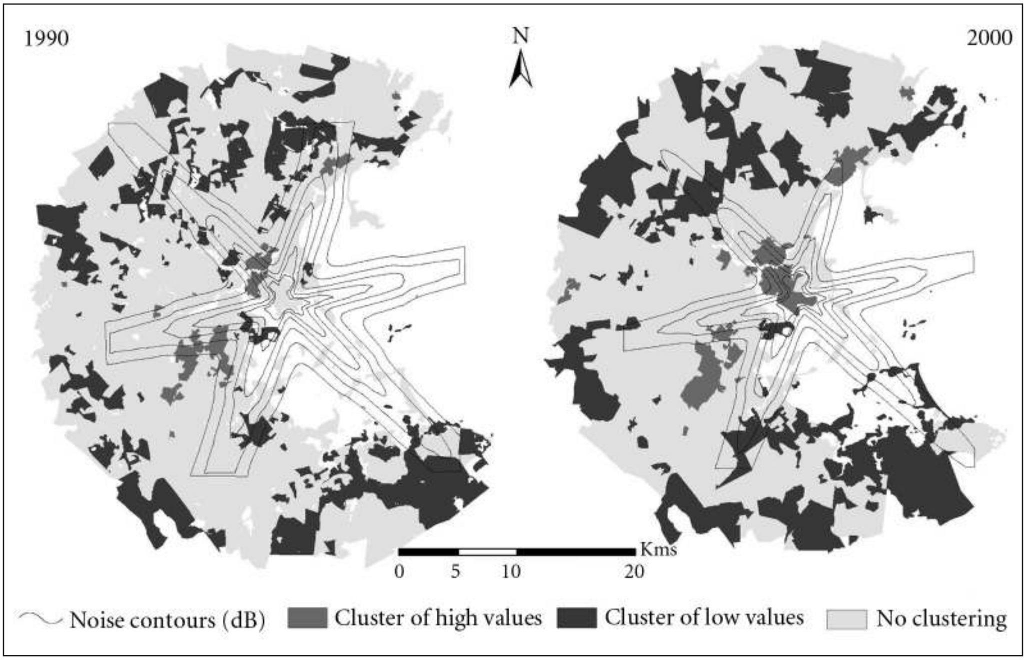

Figure 4. Spatial clusters of block groups with similar high or low percentages of Hispanic population, 1990 and 2000 (statistically significant at the 95 per cent level)

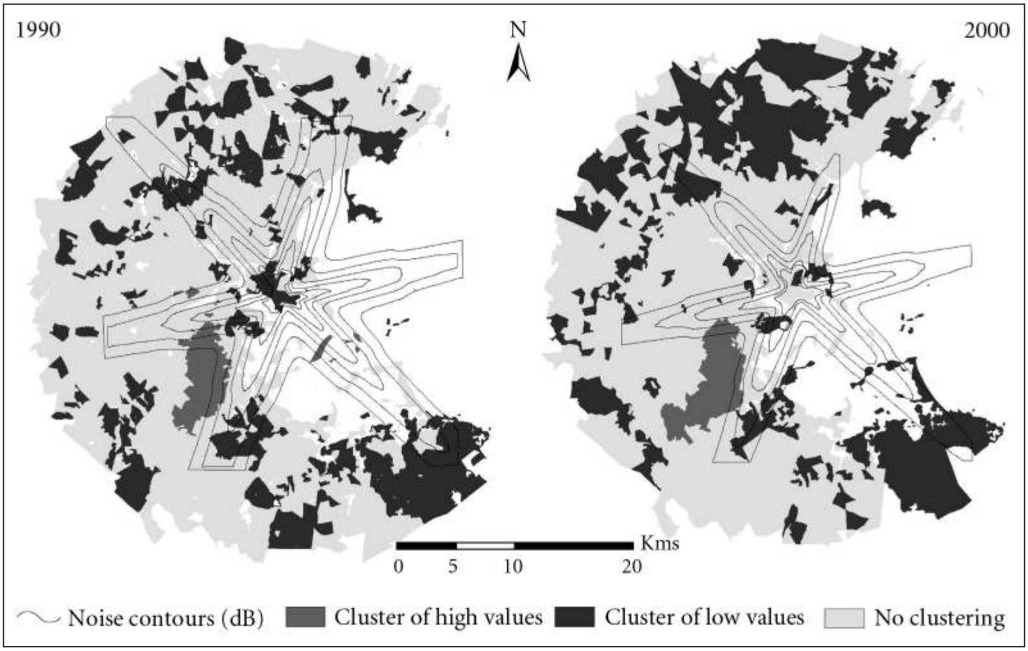

Figure 5. Spatial clusters of block groups with similar high or low percentages of Black population, 1990 and 2000 (statistically significant at the 95 per cent level)

70–75 dB. The mean values for four socio-demographic indicators were calculated for each noise range for the two years using the aforementioned aerial interpolation method and table statistics utilities in ArcGIS software. Results of the analysis are presented in Figures 6–9.

4. Results and Discussion

4.1 Affected versus Non-affected Population

As airplane designs have improved, the level of noise they produce has declined, which is illustrated by the ‘shrinking’ of the noise contours between 1990 and 2000. Based on the measurements in the GIS, on average, year 2000 contours have shifted about 100–200 metres closer to the airport in comparison with the 1990 contours. As a consequence, the percentage of people living in the study area who were affected by the airport noise was reduced from 39 per cent in 1990 to 27 per cent in 2000.

When noise-affected areas are compared with adjacent quiet areas, significant differences can be observed in the socio-demographic variables in both 1990 and 2000; in the noise-affected areas, median household income is 25–30 per cent lower and median house value is 15–20 per cent lower (Table 1). These findings are consistent with other research on environmental justice (Forkenbrock and Schweitzer, 1999). The percentage of Hispanics in the noise-affected areas was twice as high in 1990 and about three times higher in 2000 than in the quiet areas. However, the distribution of the Black population did not follow this trend. In 1990, the percentage of Blacks in the noise-affected areas was 11.51 per cent. In 2000, that percentage dropped to 6.62 per cent and was actually lower than the 9.1 per cent in the quiet areas. This could be possibly explained by the much higher growth rate of the Hispanic population than the Black population in the metropolitan Boston area between 1990 and 2000.

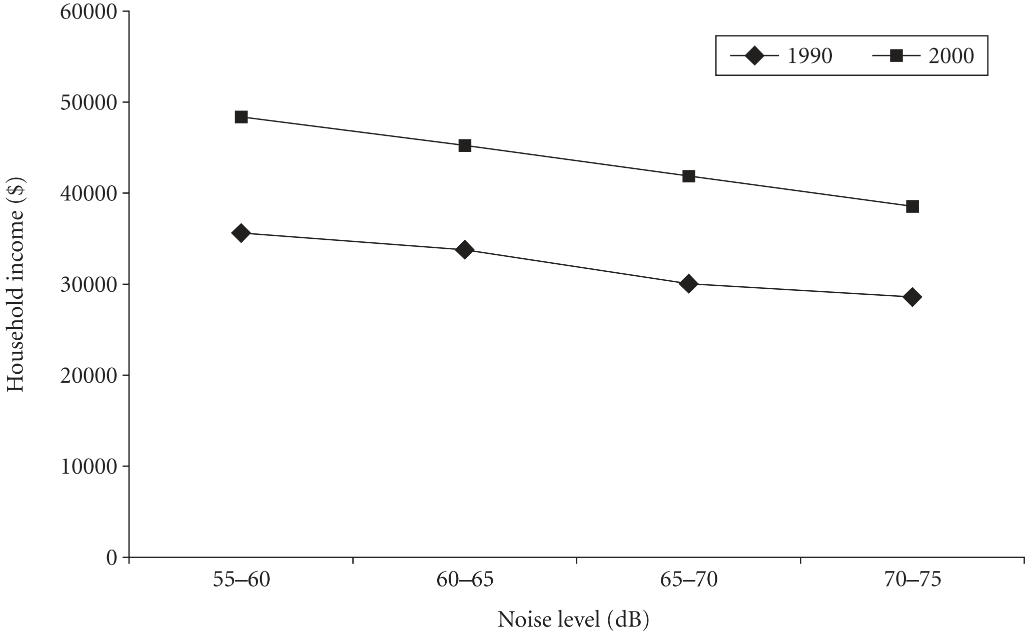

Figure 6. Median household income for different noise levels, 1990 and 2000

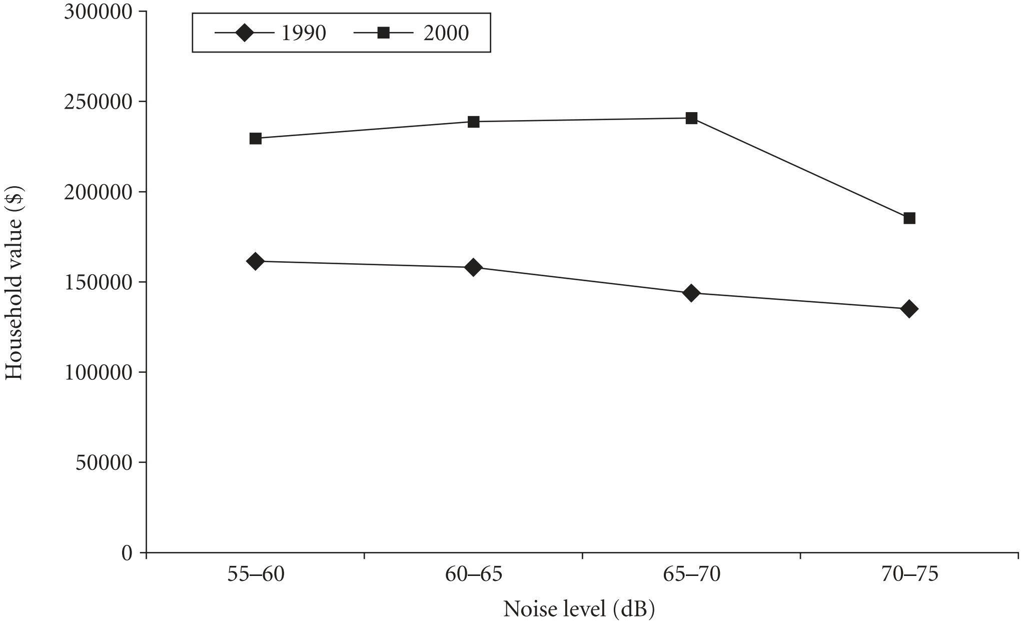

Figure 7. Median house value for different noise levels, 1990 and 2000

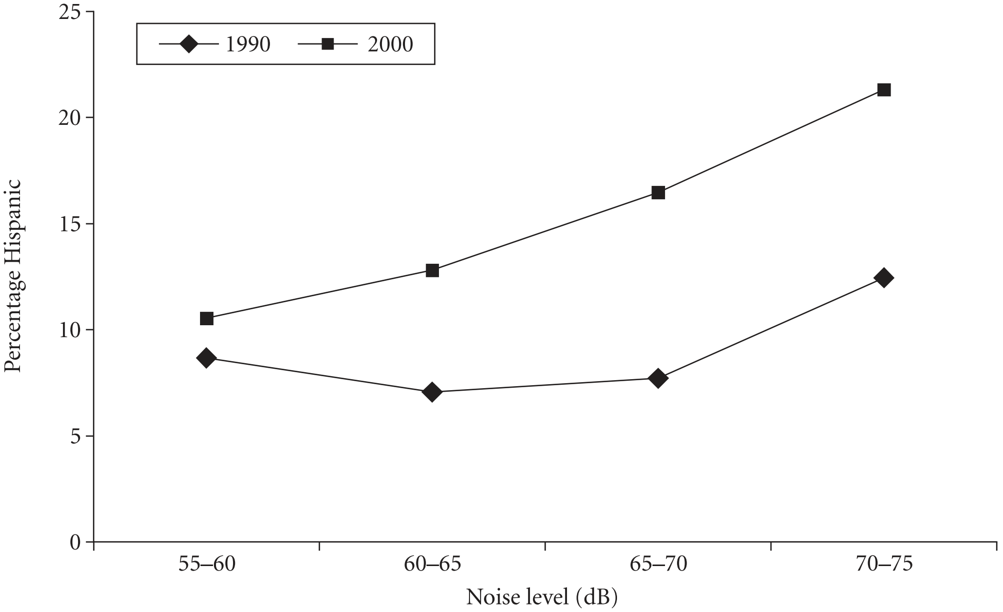

Figure 8. Mean percentage of Hispanics for different noise levels, 1990 and 2000

4.2 Comparing Socio-demographic Clusters with the Noise Level

Figure 2 shows clusters of higher house values located mostly at the periphery of the study area. Most of the clusters are outside the lowest noise contour and only a few of them fall inside the noise-affected area where the level of noise is not higher than 65 dB.

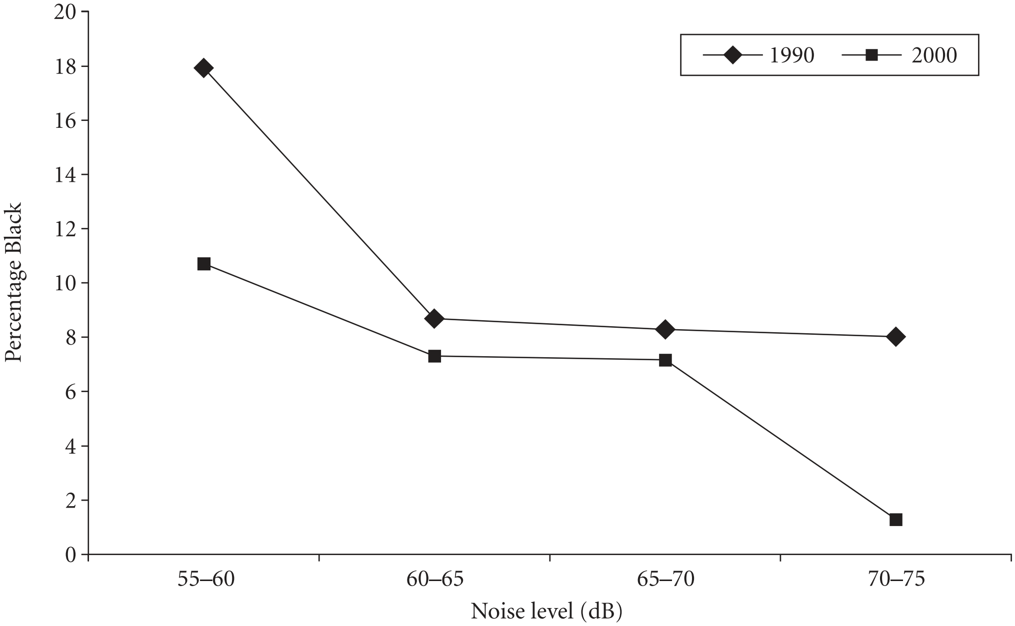

Figure 9. Mean percentage of Blacks for different noise levels, 1990 and 2000

On the other hand, clusters of low house values align well with the noise contours. Almost all of the low house value clusters in 1990 were within the noise-affected area. Additional low-value clusters appeared in 2000, both inside and outside the noise-affected area. In both years, there were large clusters of low values in the immediate vicinity of the airport where the noise levels are 70 dB and higher. The overall spatial arrangement of clusters in 1990 and 2000 is very similar. The difference is that the size and the number of the clusters have grown, especially clusters of low house values. This indicates that in 2000 there were larger contiguous areas of low-value houses in Greater Boston than in 1990.

Clusters of median income are shown in Figure 3. Their distribution is almost identical to the distribution of clusters of house values: low values are predominantly located in the noise-affected areas of Boston, Winthrop, Chelsea, Everett and Lynn and high values are located in the Boston suburbs of Cambridge, Brookline, Newton, Winchester, Lexington and Belmont. Both types of cluster have also grown in size, suggesting that there has been further concentration and spatial segregation of poverty and wealth in the study area.

Spatial clustering of minority populations is very different from the previous two indicators (Figures 4 and 5). Numerous clusters of low Hispanic and Black population percentages are located on the periphery of the study area in both 1990 and 2000, reflecting the predominantly White population in the suburbs. Most of the clusters that have a high percentage of Hispanics are concentrated in the noise-affected areas of Boston, Lynn and Chelsea, with one cluster in the immediate vicinity of the airport. Generally, the location of these high-percentage clusters has not changed between 1990 and 2000, but they have grown in size. There is only one, very large, cluster with a high percentage of Black population in the whole study area and it is located outside the noise-affected area. This cluster is in Roxbury-Roslindale, an area with a historically large Black population. This cluster did not change in location or size between 1990 and 2000, which suggests that there was little geographical mobility of the Black population in the area.

4.3 Analysing Socio-demographics within the Noise-affected Area

As we hypothesised, median household income and house value declined as the noise level increased in both years. Interestingly, the rate of the decrease of income was the same in 1990 and 2000 as illustrated by the two almost parallel lines in Figure 6. The housing value displayed a different trend in 2000: there was a slight increase in value (about $10 000 more) between the 55–60 dB and 65-70 dB noise levels and then an abrupt decline (about $55 000 less) in areas with the highest noise level, 70–75 dB (Figure 7). Spatial analysis of the Hispanic population confirmed our hypothesis as percentages increased along with the noise level in both years (Figure 8). However, the rate of increase from the less-affected to the most-affected areas was higher in 2000 than in 1990: it increased from 9 per cent to 13 per cent in 1990 and from 11 per cent to 21 per cent in 2000. The Black population showed an opposite spatial distribution which is contradictory to our hypothesis. The percentage of Blacks was the highest in the low-noise areas and the lowest in the high-noise areas (Figure 9). This trend was observed in both 1990 and 2000. This phenomenon could possibly be explained by the fact that the Black population has historically settled in certain areas of metropolitan Boston, which happened to be in low-noise areas. The fact that there was just one statistically significant cluster of high Black population in the whole study area, whose location and size has not changed between 1990 and 2000 (Figure 5) also supports this explanation.

5. Conclusions

The results of this study suggest that the cost of noise from Boston's Logan Airport does fall disproportionately on minority and low-income populations, and that there was no considerable change in the identified spatial trends and patterns between 1990 and 2000. The GIS-based techniques of spatial overlay and spatial statistics enabled us to reveal a high degree of spatial coincidence between clusters of vulnerable population, as represented by four census characteristics, and high noise level. However, by no means should this high level of spatial association imply a direct causal relationship between the noise level and the socioeconomic variables. Instead, these results should be viewed as a way to draw the attention of both policy-makers and the public to the most vulnerable people in the airport's vicinity as new policies for noise abatement are being developed and modified. Current policies and programmes of noise abatement (for example, residential and school sound-insulation programmes) do not have any provisions based on the ethnic and socioeconomic characteristics of exposed population. Currently, the only eligibility criteria for participation in these programmes is the spatial location of residence in relationship to noise-level contours. Statistically significant 'hot' and 'cold' socio-demographic spots correspond to spatial concentrations of certain types of people, representing various vulnerability levels among them. This information should be carefully considered and taken into account by regional transport and planning boards as they develop new or update existing noise-abatement policies. The income level of the affected population should become particularly important if governmental funding for noise abatement programmes is cut and/or is insufficient to serve the entire affected population. We argue that low-income populations should be given priority in this case, as they would have no means to sound insulate or sound proof their residences.

The most important contribution of this paper to the current literature on environmental justice and equality is the new methodology for determination of the noise-affected and vulnerable population. GIS provides not only an excellent visualisation environment, but most importantly it offers techniques rooted in robust tests of statistics that allow for an unbiased spatial analysis. The methodology proposed in the paper can be readily applied in any area where there is a negative technological impact and population vulnerability assessment is needed.

Future work based on this methodology should include comparative time-series analysis of other large airports in order to answer the following questions. Does the cost of noise from the airports always fall disproportionately on minority and low-income populations? Are there certain regions where there is no spatial clustering of socio-demographic characteristics around airports? And how can these results better serve the national and state policy agendas with respect to the noise abatement efforts?

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