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Using geographical information systems and spatial microsimulation for the analysis of health inequalities

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The paper presents a spatial microsimulation approach to the analysis of health inequalities. A dynamic spatial microsimulation model of Britain, under development at the Universities of Leeds and Sheffield, uses data from the censuses of 1971, 1981 and 1991 and the British Household Panel Survey to simulate urban and regional populations in Britain. Geographical information systems and spatial microsimulation are used for the analysis of health inequalities in British regions in a 30 year simulation. The interdependencies between socio-economic characteristics and health variables such as limiting long-term illness are discussed. One of the innovative features of the model is the estimation of variables such as household income at the small area level, which can then be used to classify individuals. The health situation of different simulated individuals in different areas is investigated and the role of socio-economic characteristics in determining health is evaluated.

Keywords

geographical information systems, income and health inequalities, small area microdata, spatial microsimulation

Introduction

This paper demonstrates how geographical information systems (GIS) can be combined with spatial microsimulation methodologies to investigate health inequalities and their possible interdependencies with socio-economic variables. In particular, the paper shows how a GIS-based spatial microsimulation model has been used to simulate a detailed social survey of households at the small area level in the United Kingdom (UK) on the basis of existing data from various public sector sources.

Microsimulation can be defined as a methodology that is concerned with the creation of large-scale simulated population microdata sets for the analysis of policy impacts at the micro level. In particular, microsimulation methods aim to examine changes in the life of individuals within households and to analyse the impact of government policy changes for each simulated individual and each household. Geographical microsimulation techniques involve the merging of census and survey data to simulate a population of individuals within households (for different geographical units), whose characteristics are as close to the real population as it is possible to estimate [1–3]. Dynamic microsimulation involves forecasting key socio-economic variables into the future based either on current trends or on the consequences of different policy scenarios.

One of the main objectives of the research presented in this paper is to explore health-related variables that are included in existing survey datasets such as the British Household Panel Survey (BHPS) and to combine them with geographical census data. This paper shows some examples of how it is possible to add a geographical dimension to surveys containing extremely useful and policy-relevant health variables.

A spatial microsimulation approach to generating health-related population microdata

Microsimulation is a technique that has long been established in the social sciences and has been widely used by governments around the world for the analysis of redistributive policies and budget changes. Nevertheless, there have been very few examples of extending these simulation models to enable the estimation of geographical impacts of different scenarios.

Microsimulation has been mainly developed and used by economists and there have been relatively few examples of geographical microsimulation. Figure 1 shows the results of a basic keyword search in the *Sciencedirect* academic journal database, searching the word ‘microsimulation’ in the titles or abstracts of papers in the last 30 years. As can be seen, the majority of the papers were in economics (41 per cent) with very few papers in geography (3 per cent). There is also a relatively high number of microsimulation applications in medicine. However these are applications of a different nature, as their main focus is the effectiveness of medicines (e.g. simulating the impact of medicines).

Various types of microsimulation model can be distinguished [4]. For instance, there are *static models* that are based on simple snapshots of the current circumstances of a sample of the population at any one time, and *dynamic models* that vary or age the attributes of each micro-unit in a sample to build up a synthetic longitudinal database describing the sample members’ lifetimes into the future. The main characteristic of dynamic models is that they incorporate behavioural responses under different policy scenarios. In addition, microsimulation models can become *geographical* when spatial information about the simulated entities is available (or estimated).

Spatial microsimulation involves the creation of large-scale population microdata sets and the analysis of policy impacts at the micro level. *Population microdata* contain information on individuals rather than aggregate data. Population microdata can be separated into *individual microdata* which contain information on individuals, and *household*

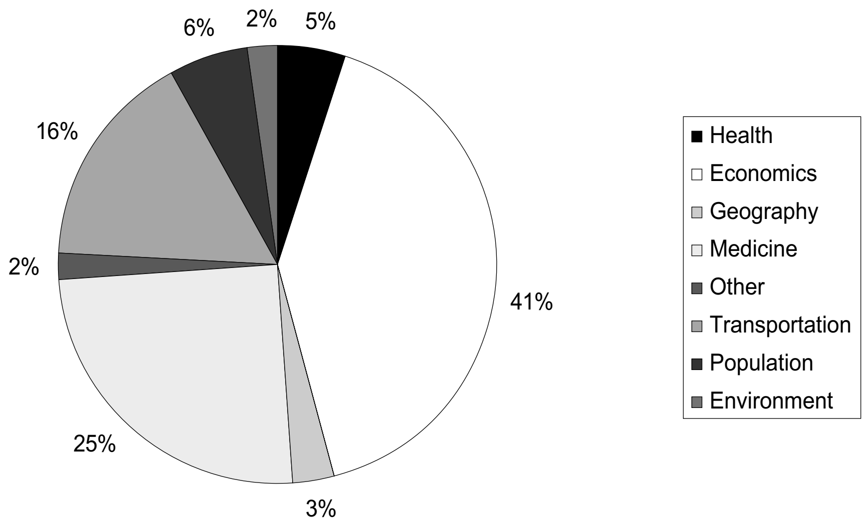

Figure 1 Distribution of microsimulation academic studies in the period 1967–2003 (source: http://www.sciencedirect.com/)

microdata which may contain household information only or may contain both individual and household information. In the context of this paper, the British Household Panel Survey (BHPS) has been used in combination with census small area data to estimate health-related variables at the small area level, as well as to explore the interdependencies of these variables with socio-economic variables such as income, social class, access to health services, etc. The BHPS is a representative longitudinal survey on the social situation of private households and may be presented in the format of a list of individuals within households (see Tables 1 and 2).

Table 1 The BHPS microdata format

PERSON	**HID*	*PID*	**AGE12*	*SEX*	**JBSTAT*	…	**HLLT*	**QFVOC*	**TENURE*	**JLSEG*	…
1	1000209	10002251	91	2	4	…	1	1	6	9	…
2	1000381	10004491	28	1	3	…	2	0	7	–8	…
3	1000381	10004521	26	1	3	…	2	0	7	–8	…
4	1000667	10007857	58	2	2	…	2	1	7	–8	…
5	1001221	10014578	54	2	1	…	2	0	2	–8	…
6	1001221	10014608	57	1	2	…	2	1	2	–8	…
7	1001418	10016813	36	1	1	…	2	1	3	–8	…
8	1001418	10016848	32	2	–7	…	2	–7	3	–7	…
9	1001418	10016872	10	1	–8	…	–8	–8	3	–8	…
10	1001507	10017933	49	2	1	…	2	0	2	–8	…
11	1001507	10017968	46	1	2	…	2	0	2	–8	…
12	1001507	10017992	12	2	–8	…	–8	–8	2	–8	…

Table 2 Variable descriptions for Table 1

PERSON	Person number
*HID	Household identifier (number of household to which the listed individual belongs)
PID	Person identifier (a unique number to identify the individual)
*AGE12	Age at 1 December X
SEX	Sex
*JBSTAT	Current labour force status (e.g. self-employed, in paid employment, unemployed, family care etc.) in year X
*HLLT	Health status in year X
*QFVOC	Vocational qualifications in year X
*TENURE	Tenure status in year X
*JLSEG	Socio-economic group: last job (in year X)

Geographical microsimulation techniques involve the merging of survey data such as the BHPS with census and other geographical area data to simulate a population of individuals within households (for different geographical units), whose characteristics are as close to the real population as it is possible to estimate. In other words, geographical microsimulation models simulate *virtual populations* in given geographical areas, so that the characteristics of these populations are as close as possible to their 'real-world' counterparts. One of the major advantages of microsimulation is that it can be a substitute for conducting detailed surveys to produce survey data such as the BHPS described above at the small area level.

The spatial microsimulation method typically involves three major procedures:

- The construction of a microdata set from samples and surveys.
- *Static* what-if simulations, in which the impacts of alternative policy scenarios on the population are estimated: who would benefit from a particular local or national government policy? Which geographical areas would benefit the most?
- *Dynamic* modelling, to update a basic microdata set and future-oriented what-if simulations.

The first procedure can also be defined as static spatial microsimulation. This involves the reweighting of an existing microdata sample (which is only available at coarse levels of geography), so that it would fit small area population statistics tables. For instance, an existing microdata set such as the BHPS described above can be reweighted to 'populate' small areas. The BHPS provides a detailed record for a sample of households and all of their members. Reweighting methods aim to sample from all the microdata records to find the set of household records that best matches the population described in the UK Small Area Statistics. First, a series of small area tables (e.g. from the census or other sources) that describe the small area of interest must be selected. For example, a reweighting method would sample from the BHPS to find a suitable combination of households that would fit the statistical data in two hypothetical areas or neighbourhoods within cities and regions presented in Table 3.

Table 3 A hypothetical small area statistical dataset for two areas

Small area table (a): household type	*Small area table (b): economic activity of household head*	*Small area table (c): tenure status*
Area 1	*Area 1*	*Area 1*
60 married couple households	80 employed/self-employed	60 owner occupier
20 single-person households	10 unemployed	20 local authority or housing association
20 other	10 other	20 rented privately
Area 2	*Area 2*	*Area 2*
40 married couple households	60 employed/self-employed	60 owner occupier
20 single-person households	20 unemployed	20 local authority or housing association
40 other	20 other	20 rented privately

The task would be to select the records of the BHPS microdata that best match these statistical descriptions using statistical matching or geographical microsimulation reweighting techniques [5, 6]. However, there are a vast number of possible sets of households that can be drawn from the BHPS sample. A wide range of techniques can be employed to find a set that fits the target tables well.

Dynamic microsimulation involves forecasting past changes forward to produce as good an estimate as possible of an individual's circumstances in the future – were current trends to continue, or were they to change under different policy scenarios. Dynamic microsimulation typically involves the modelling of behavioural and second-order effects. This can be carried out on the basis of calculated probabilities for a series of event changes that occur during the lifetime of individuals [7].

Another aim of dynamic spatial microsimulation is the analysis of household and individual reactions and behavioural changes which may result from policy changes. This adds further to the complexity of the task [8].

The task becomes even more difficult when there are attempts to introduce geographical detail. Spatial dynamic microsimulation involves the behavioural modelling of individuals over time and at various geographical scales. It also involves the modelling of individual decisions that have a strong geographical element such as migration. The latter is dependent on a series of individual characteristics such as age, socio-economic background and tenure [9].

Spatial dynamic microsimulation involves the modelling of different types of transitions on the basis of each individual's attributes and circumstances. Nevertheless, one of the biggest problems associated with both spatial and non-spatial *dynamic* microsimulation is that they can be extremely complex and difficult to develop, implement and explain to policy practitioners who may be interested in using them. It has often been argued in the microsimulation literature that there is a need for transparency and simplicity in the construction of models. An alternative to the traditional comprehensive dynamic microsimulation models is to combine aggregate projection methods with the static microsimulation methods.

Table 4 depicts the steps that need to be followed in the procedure for modelling survival and migration. It should be noted, however, that the example depicted in Table 4 is simplified in order to illustrate the process.

One of the inherent difficulties of such a task is to determine the interdependencies between individual attributes and events. For instance, the probabilities of an individual participating in the labour force may be conditional upon family status (e.g. having children). However, it may also be argued that family status depends on labour market status [10].

An additional difficulty associated with dynamic spatial microsimulation models is the lack of sufficient geographical data that would enable the simulatation of interactions such as migration flows between areas (e.g. there are no microdata on migration that would enable a reasonably accurate simulation of migration into the future). Due to the lack of suitable data there have been very few examples of spatial microsimulation of events such as migration [11, 12].

An object-oriented spatial microsimulation approach to the analysis of health inequalities

In the context of the research presented in this paper we have developed and used an object-oriented household simulation model built in Java. As discussed above, spatial microsimulation frameworks have the advantages of a list-based approach to microdata representation. In such frameworks, variables are treated as lists rather than matrices. For instance, in the context of a microsimulation approach a household or an individual has

Table 4 A simple example of the microsimulation procedure for the modelling of migration and survival

Steps	*1st*	*2nd*	…	*Last*
Age, sex and marital status and location (e.g. neighbourhood or small area level) (given)	Age: 25 Sex: male Marital status: single GeoCode: Neighbourhood 1	Age: 76 Sex: female Marital status: married GeoCode: Neighbourhood 2	…	Age: 30 Sex: male Marital status: married GeoCode Neighbourhood 3
Probability (conditional upon age, sex, location) of hh to migrate	0.30	0.05	…	0.26
Random number	0.2	0.4	…	0.6
Migration status assigned on the basis of random sampling	Migrant	Non-migrant	…	Non-migrant
Probability (conditional upon age, sex, location) of hh to survive	0.9	0.8		0.9
Random number	0.5	0.9	…	0.4
Survival status	Survived	Deceased	…	Survived

a list of attributes which are all stored as lists rather than as occupancy matrices [3]. It has long been argued that from a computer programming perspective, the individuals and households can also be seen as objects with their associated object or instance variables (attributes).

An object-oriented language such as Java or C++ is most suitable for microsimulation modelling. Object orientation can be seen as a conceptual tool that can be used to better understand and analyse different regional systems. In particular, objects can be seen as abstractions of the essential aspects of a regional science domain and they can be easily distinguished from one another in form and function. In an object-oriented system, a class is a collection of data and methods that operate on that data [13]. Further, the data and methods describe the state and behaviour of an object [13–16]. Classes can also be seen as templates for multiple objects with similar features. They embody all the features of a particular set of objects. Hence, we can have a household class that describes the features of all households (e.g. age, sex and marital status of head of household, tenure, etc.).

The household class serves as an abstract model for the concept of a household. Once a household class is defined then lots of different instances of that class can be created and each different household instance can have different features while still being immediately recognizable as a household. Further, in an object-oriented system a class can be extended via the inheritance mechanism in order to be used in different problem domains. In particular, a class can inherit all of the properties of a superclass and is distinguished from its superclass by new and distinctive features and properties. For instance, a household class in a labour market model may have an initial set of attributes (e.g. sex, age, socio-economic status) and functions or behaviours (e.g. job-search and job-change behaviours).

However, if the labour market model was to be extended, so that it would take into account the consumption patterns of households and their shopping behaviour, it would be possible to define a new household subclass that would extend the initial household via the inheritance mechanism. Thus, the new household subclass would inherit all of the properties of its superclass and would have additional properties (such as health status, access to health services, access to private health care) and behaviours.

Similar extensions could be made to the household class in order to model migration or residential search patterns. Further, there are other characteristics of the object-oriented approach that can be advantageous in a geographical and regional science framework (for a more detailed discussion and examples see [13, 17]). Taking advantage of the available object-oriented technologies, we have used Java (which has, amongst other benefits, the added advantage of platform independence) to statically microsimulate individuals and households. The overall goal of the model was to use all the classes to create individual and household objects.

The model built in the context of the research presented here reads data from various sources in order to create individual and household objects. In particular, it adopts a spatial microsimulation methodology such as that described in the previous section in order to reweight the BHPS data and create household and individual classes at the small area level. Tables 5 and 6 provide an illustration of the individual and household classes.

At the heart of our modelling approach lies a 'reweighter' class which is used to read input survey data (from the UK census of population and the BHPS) in order to create household and individual classes (as described in the tables), resulting in estimating new information (including health-related information) at the small area level.

The simulation results in the creation of a small area population microdata set containing a wealth of health-related variables, as well as socio-economic variables, providing the enabling environment for an investigation of the interdependencies between these variables. The output data are read into the ArcGIS software for further analysis and mapping. The following section gives a flavour of some of the model outputs.

Simulation outputs

In this section we present some preliminary results of the modelling approach that we have adopted and implemented for the city of York, England. In order to explore the likely possible relationships between health variables and the socio-economic status of different types of individuals and households, we classified the simulated households into the following five groups:

- *very poor*, comprising all households with equivalized income below or equal to half the median income of York
- *poor*, comprising all households with equivalized income greater than half the median and smaller than or equal to three-quarters of the median
- *below average*, comprising all households with equivalized income greater than three-quarters of the median and smaller than or equal to the median
- *above average*, comprising all households with equivalized income greater than the median and smaller than or equal to the median plus a quarter of the median
- *affluent*, comprising all households with equivalized income greater than the median plus a quarter of the median.

Table 7 shows the absolute and relative sizes of each household class throughout the simulation period for the city of York.

Table 7 The size of the simulated household classes, 1991–2021

	Very poor	*Poor*	*Below average*	*Above average*	*Affluent*	*Total no. households*
Class size by year						
1991	7,190	7,149	6,589	5,322	15,605	41,855
2001	8,208	9,373	6,020	6,753	16,848	47,202
2011	9,085	9,149	7,303	8,293	17,244	51,074
2021	11,700	6,222	9,476	11,185	16,213	54,796
Class size (% all households) by year						
1991	17.2%	17.1%	15.7%	12.7%	37.3%	100.0%
2001	17.3%	19.9%	12.8%	14.3%	35.7%	100.0%
2011	17.8%	17.9%	14.3%	16.2%	33.8%	100.0%
2021	21.3%	11.4%	17.3%	20.4%	29.6%	100.0%

It should be noted that the power of spatial microsimulation modelling frameworks lies in their ability to estimate policy-relevant variables at the small area level for which published data do not exist. For instance the following health-related variables are included in the BHPS but are not available at the small area level (e.g. postal sector, neighbourhood):

- personal health condition
- visits to doctor
- hospital/clinic use
- use of health/welfare services
- social services
- specialists
- check-ups/tests/screening
- smoking
- caring for relatives/others
- time spent caring for others
- private medical insurance.

Here is an example of some of the health-related questions asked by the BHPS in order to generate data pertaining to the above variables:

- AHLSTAT: health over last 12 months. (Think back over the last 12 months about how your health has been – compared to people of your own age, would you say that your health has on the whole been: excellent, good, fair, very poor?)
- AHLZEST: energy compared with people of same age.
- AHLPRB: health problems – none, individual.

This kind of data can be extremely useful for health-related geographical applications (e.g. calculated catchment areas of hospitals and health centres). However, the BHPS data are only available at relatively coarse levels of geography (standard region or metropolitan district). In the context of this paper we have spatially microsimulated the BHPS so that estimates of the above health-related variables can become available at small area levels (in our case the city level, as well as intra-city: electoral wards).

Such variables can be estimated at the small area level and cross-tabulated with socio-economic variables in order to investigate any possible interdependencies and associations. The aim here is to build upon past work in health geography [18] that investigated the link between health and poverty and examined these issues for different parts of the UK. In particular, Curtis looked at illness and mortality differences in relation to various indicators of socio-economic status and for different age groups in different UK regions. Similar examples include a model [19] that investigated how the 'health gap' in Britain could be narrowed if different social policies were implemented. In particular, the authors estimated the impact of changes to the population in different areas of Britain under three different policy scenarios: *modest redistribution of 'wealth'; achieving 'full employment';* and *eradicating 'child poverty'*. They also estimated the combined effect that these policies would have upon the populations of each British parliamentary constituency.

This paper aims at extending this kind of work by generating a powerful geographical health information database. Some spatial microsimulation outputs and examples are useful at this stage to back up the arguments made above. Table 8 shows a selection of estimated and project variables for households classified as ‘very poor’ for the city of York, and Table 9 shows similar variables for households classified as ‘affluent’. As can be seen, 9 per cent of the individuals living in very poor households are simulated to report limiting long-term illness (LLTI) in 1991, and this is simulated to decrease to 7.9 per cent in 2021. The LLTI rates are slightly lower for the affluent group.

It should be noted that these tables show some preliminary results of the model. The aim here is to give an indication of the health-related information that can be simulated geographically and through time with the use of spatial microsimulation. For instance, it clearly is very unlikely that no one will have a drug or alcohol problem in 2021.

One of the major advantages of frameworks based on GIS spatial microsimulation is the ability to create thematic maps of the simulated information and to explore whether there is any spatial pattern. Figure 2 shows the spatial distribution of the simulated individuals reporting no health problems in York. In addition, Figure 3 shows the spatial distribution of estimated household income in York. As can be seen the geographical pattern is very similar, giving an indication that the geographical areas of York with the

Table 8 Living standards of very poor households

	1991	*2001*	*2011*	*2021*
Households (% of all households in York)	17.2%	17.3%	17.8%	21.3%
Individuals (% of all individuals in York)	14.7%	13.3%	13.7%	20.5%
LLTI (as % of all individuals in very poor households)	9.0%	7.3%	5.4%	7.9%
Elderly (over 64 years as % of all individuals in very poor households)	30.1%	32.0%	33.3%	44.2%
Reporting anxiety and depression (% of all individuals in very poor households)	10.6%	10.3%	7.4%	3.1%
Reporting health problems with alcohol or drugs (% of all individuals in very poor households)	0.9%	1.1%	0.3%	0.0%

Table 9 Living standards of affluent households

	1991	*2001*	*2011*	*2021*
Households (% of all households in York)	37.3%	35.7%	33.8%	29.6%
Individuals (% of all individuals in York)	36.5%	35.0%	33.0%	29.3%
LLTI (as % of all individuals in group)	6.6%	4.1%	2.3%	1.8%
Elderly (over 64 years as % of all individuals in group)	13.3%	13.7%	21.0%	23.0%
Reporting anxiety and depression (% of all individuals in group)	5.7%	4.8%	2.0%	1.1%
Reporting health problems with alcohol or drugs (% of all individuals in group)	0.0%	0.0%	0.0%	0.0%

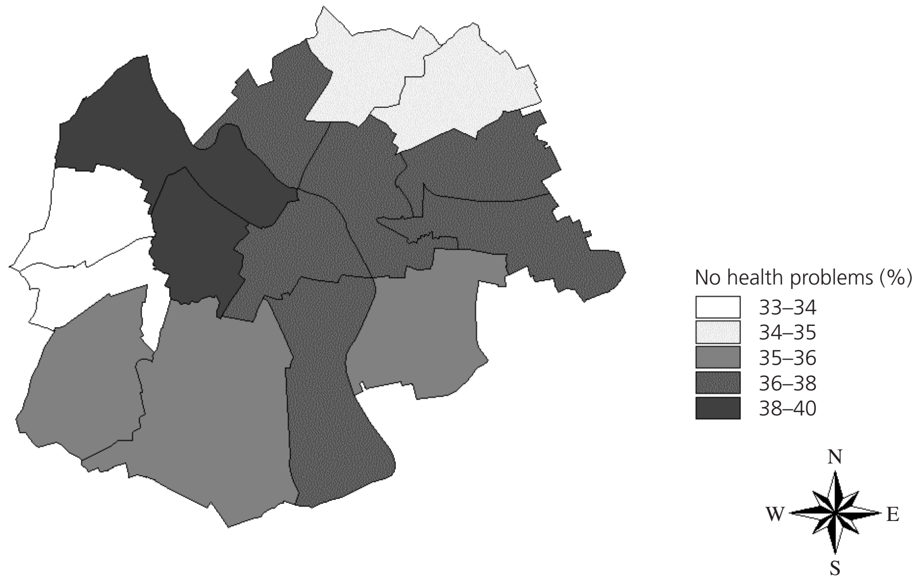

Figure 2 Simulated geographical distribution of individuals reporting 'no health problems' in York

highest income levels also have the highest numbers of individuals reporting 'no health problems' according to our simulation.

It is also interesting to look at the average income of the simulated individuals reporting health problems and no health problems respectively. This is shown in Table 10. As can be seen, the average annual income of individuals reporting no health problems is higher.

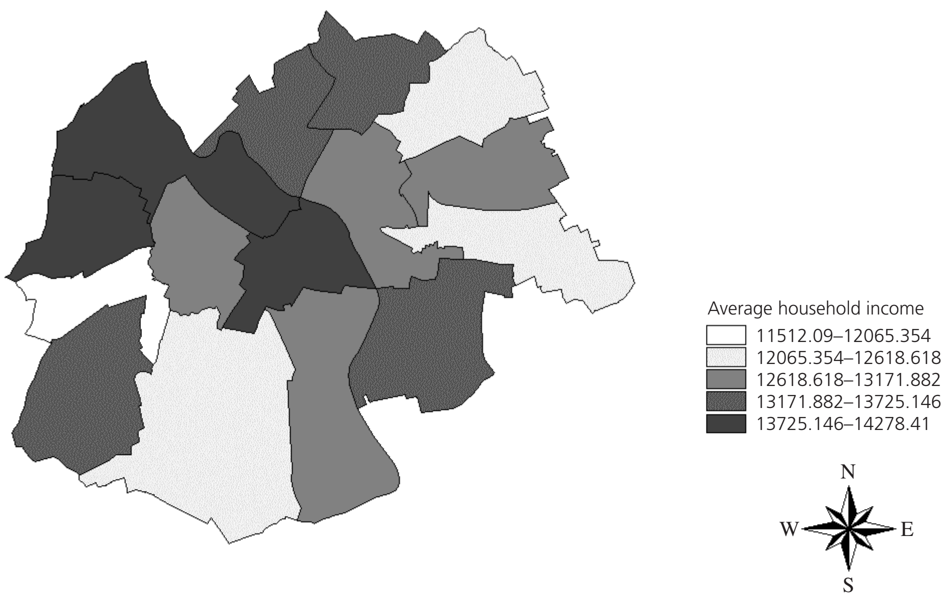

Figure 3 Simulated geographical distribution of average household income in York

Table 10 Simulated average income of individuals with and without 'health problems'

	Average income
No health problems	£14,188.49
Health problems	£11,613.83

Figure 4 depicts a scatterplot of the data for LLTI and income and also presents a fitted regression line on the basis of these limited datasets for the 15 electoral wards of York. Nevertheless, it should be stressed that the results presented here are exploratory and that there is a need for a more robust and sophisticated statistical analysis of the simulation outputs in order to reach any meaningful conclusions regarding the relationship of socio-economic variables such as income and wealth with health status.

In addition, there is a need for systematic sensitivity analysis in order to examine the degree of confidence to which the health-related variables in the BHPS can be estimated. Figure 5 gives an example of how such a validation exercise could be carried out, by providing a scatterplot of simulated versus actual (observed from the census of population) rates of LLTI. It would be reasonable to expect that the performance of the model would vary from variable to variable, especially at areas as small as wards, and for variables which were not included as constraints in the simulation exercise (more details on validation methods of the model presented here and examples appear in [20]).

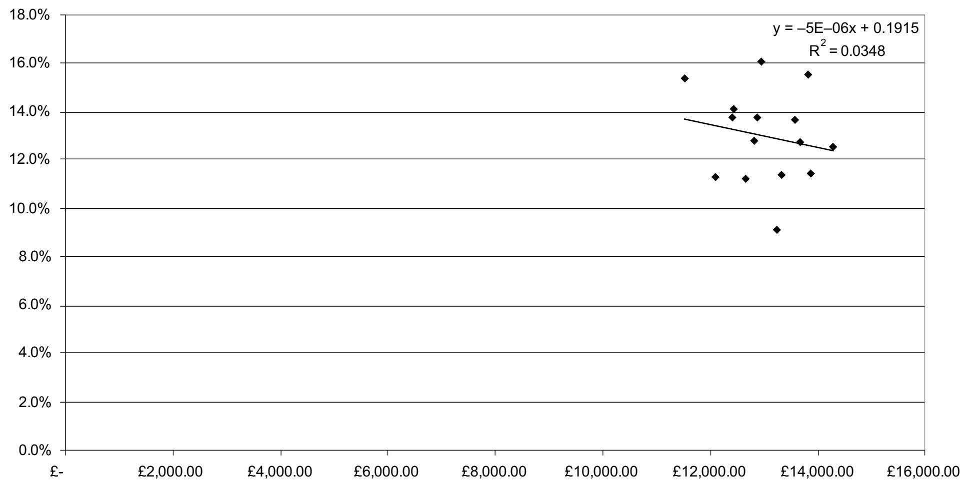

Figure 4 Relationship between 'no health problems' and income in York

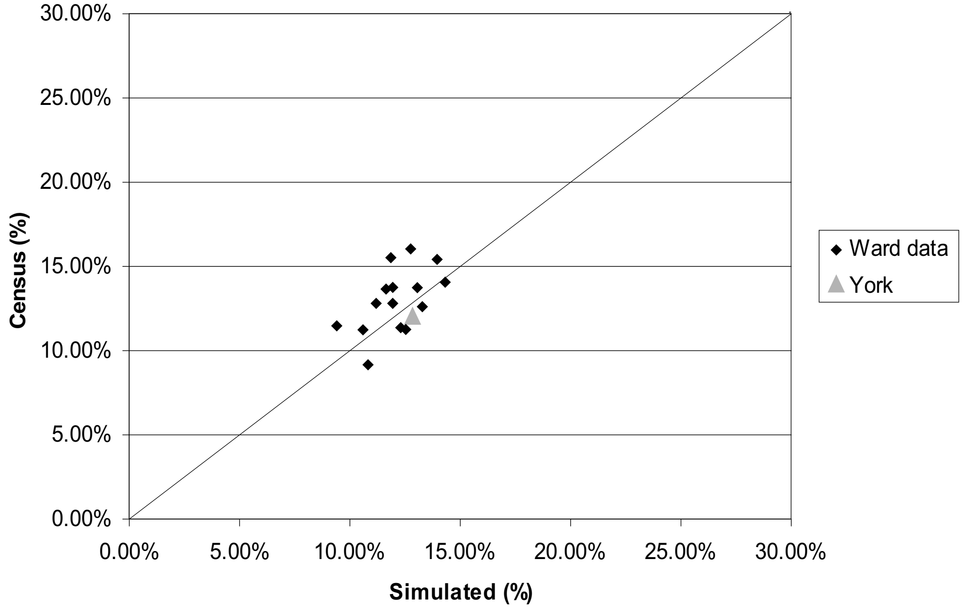

Figure 5 Simulated versus actual rates of limiting long-term illness, York, 1991

Conclusions

In this paper we have presented a prototype method for the geographical analysis of survey and census data. This method was developed on the basis of previous work in the area of microsimulation.

Overall, it can be argued that the geographical microsimulation method presented in this paper can be used to provide useful information on health-related variables and socio-economic trends that could be extremely useful in health-related applications. However, it should be noted that the spatial microsimulation method proposed and implemented in this paper has a great deal of potential for further improvement. Amongst our immediate priorities is to include more regional and local subsystems into the simulation framework, including the location and characteristics of hospitals and health centres.

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References

1 Williamson P, Birkin M, Rees P. The estimation of population microdata by using data from small area statistics and samples of anonymised records. *Environment and Planning A* 1998; **30**; 785–816.
2 Ballas D, Clarke G P. Towards local implications of major job transformations in the city: a spatial microsimulation approach. *Geographical Analysis* 2001; **33**; 291–311.
3 Clarke G P. Microsimulation: an introduction. In Clarke G P ed. *Microsimulation for Urban and Regional Policy Analysis* 1–9. London: Pion, 1996.
4 Mertz J. Microsimulation: a survey of principles, developments and applications. *International Journal of Forecasting* 1991; **7**; 77–104.
5 Sutherland H, Taylor R, Gomulka J. Combining household income and expenditure data in policy simulations. Review of Income and Wealth 2002; 48; 75–94.
6 Ballas D, Rossiter D, Thomas B, Clarke G P, Dorling D. *Geography Matters: Simulating the Local Impacts of National Social Policies*. York: Joseph Rowntree Foundation, 2005.
7 Gilbert N, Troitzsch K G. *Simulation for the Social Scientist*. Buckingham: Open University Press, 1999.
8 Redmond G, Sutherland H, Wilson M. *The Arithmetic of Tax and Social Security Reform: A User's Guide to Microsimulation Methods and Analysis*. Cambridge: Cambridge University Press, 1998.
9 Rogerson P A, Plane D A. The dynamics of neighborhood age composition. *Environment and Planning A* 1998; **30**; 1461–72.
10 Falkingham J, Lessof C. Playing God or LIFEMOD: the construction of a dynamic microsimulation model. In Hancock R, Sutherland H eds *Microsimulation Models for Public Policy Analysis: New Frontiers* 5–32. London: Suntory-Toyota International Centre for Economics and Related Disciplines, LSE, 1992.
11 Swan N. Unemployment insurance and labour mobility: analysis using a new Swedish microsimulation model. In Mitton L, Sutherland H, Weeks M eds *Microsimulation Modelling for Policy Analysis: Challenges and Innovations* 251–67. Cambridge: Cambridge University Press, 2000.
12 Ballas D, Clarke G P, Wiemers E. Building a dynamic spatial microsimulation model for the Irish rural economy. *Population, Space and Place* 2005; **11**; 157–72.
13 Jackson R W. Object-oriented modelling in regional science: an advocacy view. *Papers in Regional Science* 1994; **73**; 347–7.
14 Ballas D, Clarke G P. GIS and microsimulation for local labour market policy analysis. *Computers, Environment and Urban Systems* 2000; **24**; 305–30.
15 Wilson A G. *Complex Spatial Systems: the Modelling Foundations of Urban and Regional Analysis*. London: Prentice Hall, 2000.
16 Flanagan D. *Java in a Nutshell*. Sebastopol: O'Reilly, 1997.
17 Openshaw S, Turton I, Macgill J. Putting the geographical analysis machine on the Internet. Paper presented at GISRUK 98 Conference, 2 April 1998, Edinburgh.
18 Curtis S. Geographical perspectives on poverty, health and health policy in different parts of the UK. In Philo C ed. *Off the Map: the Social Geography of Poverty in the UK* 153–88. London: Child Poverty Action Group, 1995.
19 Mitchell R, Dorling D, Shaw M. *Inequalities in Life and Death: What If Britain Were More Equal?* Bristol: Policy, 2000.
20 Ballas D, Clarke G P, Dorling D, Eyre H, Rossiter D, Thomas B. SimBritain: a spatial microsimulation approach to population dynamics. *Population, Place and Space* 2005; **11**; 13–34.

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