Application of Geographic Information Systems and Simulation Modelling to Dental Public Health: Where Next?

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Abstract:

Public health research in dentistry has used geographic information systems since the 1960s. Since then the methods used in the field have matured, moving beyond simple spatial associations to the use of complex spatial statistics and, on occasions, simulation modelling. Many analyses are often descriptive in nature however, and the use of more advanced spatial simulation methods within dental public health remains rare, despite the potential they offer the field. This review introduces a new approach to geographical analysis of oral health outcomes in neighbourhoods and small area geographies through two novel simulation methods – spatial microsimulation, and agent-based modelling. Spatial microsimulation is a population synthesis technique, used to combine survey data with Census population totals to create representative individual level population datasets, allowing for the use of individual level data previously unavailable at small spatial scales. Agent-based models are computer simulations capable of capturing interactions and feedback mechanisms, both of which are key to understanding health outcomes. Due to these dynamic and interactive processes the method has an advantage over traditional statistical techniques such as regression analysis, which often isolate elements from each other when testing for statistical significance. This article discusses the current state of spatial analysis within the dental public health field, before reviewing each of the methods, their applications, as well as their advantages and limitations. Directions and topics for future research are also discussed, before addressing the potential to combine the two methods in order to further utilise their advantages. Overall, this review highlights the promise these methods offer, not just for making methodological advances, but also for adding to our ability to test and better understand theoretical concepts and pathways.

Keywords. Dental public health, Geography, microsimulation, agent-based, oral health, GIS, spatial

Introduction

While differing in their uses and definitions, geographic information systems (GIS) are a group of methods or applications that store, manage, retrieve, manipulate and analyse data of a geographical or spatial nature. The use of GIS to analyse health related outcomes dates back to the work of Charles Picquet[1] who mapped the presence of cholera per 1000 residents in the 48 districts of Paris in 1832. Similar pioneering work was conducted by John Snow in 1854[2], which used points on a map to depict the spatial nature of cholera related deaths in Soho, London. The modern term 'geographic information systems', and its computerised form, was developed by 'the father of GIS', Roger Tomlinson, in 1967[3], as part of a project designed to store and analyse data on land usage in Canada.

The use of GIS allows social and health related patterns to be studied within their spatial contexts, as well as offering a more easily understandable way of communicating spatial data. The use of mapping software, for example, allows for spatial data to be presented in a far more consumable way than tables of data, or text. While maps are the most commonly thought of form of GIS, there are numerous types of other GIS applications associated with these, some of which are covered in this review.

Geographic information systems have been applied in a number of public-health-related studies. This has included studies of the influence of built, physical and social environments in determining neighbourhood level resilience[4], measuring inequalities in access to shops, education, recreation, and health facilities[5], as well as associations between household and neighbourhood amenities and self-assessed health, anxiety and depression[6]. The use of GIS for the investigation of food environments has proven a popular theme, including studies investigating links between fast food locations and fruit and vegetable consumption[7], as well as the links between food retail locations, diet and body mass index (BMI) scores[8]. Within dental public health, among the more prominent themes using GIS are the estimation of access to (or distance from) dental services or oral health resources[9], or the thematic mapping and analysis of oral health[10]. Often, these articles have been of a descriptive nature; however, more advanced methods are becoming more prominent within the field, and these may offer greater insight into the topics studied within the field of dental public health[11].

Although there is a rapidly growing number of studies and applications of geographic information systems within dental public health, and continued advancement of GIS related methods in the field, there are a number of areas that are still lacking both conceptually and methodologically. The analysis of the effects of neighbourhood environments, for example, remains a relatively underdeveloped area within the dental literature. Accordingly, the aim of this review is to summarise the current state of GIS-related research within dental public health, before introducing two novel methods that could advance the spatial evidence base, and help move beyond the descriptive analyses often seen in the field. These methods (spatial microsimulation modelling and agent-based modelling) have been relatively underutilised within dental public health.

This article draws and builds upon recent efforts to highlight the potential synergies between these methods[12], but with a focus on health research and dental public health in particular. To that end, the nature of the methods is discussed, as well as previous relevant applications and examples. Advantages and limitations of the methods are highlighted, as well as a discussion of areas of future research they can help in addressing. The potential for combining the two methods for analysing oral health inequalities is also covered. This article does not include a discussion of what constitutes a neighbourhood, as there is no agreed upon definition, although reviews of the concept of place in health research are available[13].

Where are we now?

GIS studies and dental public health

There have been many GIS-based studies in Dental Public Health since the 1960s. These have covered a wide range of topics, including: dentist to patient ratios and payments[14,15]; service usage and access to services and amenities[9,16-20]; spatial variations in oral health outcomes[10,21,22]; dental workforce numbers and utilisation rates[23-25]; the spatial patterning of dental services[26-29]; the effects of interventions[30]; and contextual level influences on oral health[31-33].

These studies have used many different GIS-related methods, including: the use of concentric circles[14,15], which indicate the radii from a defined point for a certain phenomenon (e.g. service coverage); Voronoi polygons[16], whose boundaries define areas closest to a given point, relative to all other points; the use of Census and deprivation data to distinguish areas based on socio-demographic characteristics[16-19]; buffer zones used to delineate the coverage areas of services[18-19]; Euclidean (or straight line) distances between locations[18]; transportation times and station locations[26,27]; thematic mapping of oral health[10,21,22]; point based location data to compare the locations of dental services to social phenomena[9,17-19,28]; human cartograms, which depict geographical areas relative to a given variable other than land mass[28]; geographical data on interventions[30]; and the study of nested geographical data through multilevel modelling[31-33].

Such work has allowed researchers and dental public health practitioners to understand the role of spatial variation (or ‘place’) in: differences in dentist to patient ratios and associated payments[14,15]; dental service usage by schoolchildren[16]; access to dental services[9,17-19,29]; oral cancer[10]; dental trauma[21]; tooth decay[22]; dentist shortages and areas in need of new facilities[20]; dental workforce numbers[23] and potential shortfalls[19,24,25]; the clustering of dental services based on location quotients[28]; and the effects of interventions on children's oral health[30]; as well as important contextual level pathways to oral health outcomes[32] and the effects of a number of neighbourhood-based features[31,33].

Notable innovations include recent studies on dental practice locations. For example, Horner and colleagues[20] implemented a 'location set covering problem' (p.114) using GIS in their study of location based accessibility in Ohio. This allowed them to take the locations of existing practices in the state, and test a range of service catchment areas to identify zip codes that would benefit from the location of new services. They found that, when using 10-mile catchment areas, only 24 new practices would be required. A similar approach was employed by Nasseh and colleagues[19], this time in the form of a two-step floating catchment area method. This technique creates catchments around dentist locations and population centres to calculate provider-to-population ratios. This allowed the authors to surmise that geographical access to dental care differed significantly between Wisconsin and Missouri (USA), with a higher percentage of residents from the latter state living in areas considered to have a dental shortfall.

Studies such as those conducted by Feng and colleagues[23] made use of geographical statistics including spatial autocorrelation (the degree to which an object is similar to others near it), local indicators of spatial association (LISA – tests for clusters in the spatial distribution of a variable), and geographically weighted regression (regression capable of modelling local relationships between variables by taking non-stationary variables into account), which demonstrated a lack of association between dental workforces and utilisation rates in the Appalachia region of the United States. Other studies have used geographical statistics such as spatial autocorrelation to assess the clustering of dental services in urban areas[28]. Additionally, Jager and colleagues made use of geographically weighted regression to estimate losses from the dental workforce in Germany in 2030[24]. Through the use of selected socio-demographic information and data on dentist losses between 2001 and 2011, geographically weighted regression was used to determine spatial statistics for each geographical unit, allowing for estimations of future dental gains and losses across these spatial units. This demonstrated that many urban areas could be overserved relative to rural regions, with no compensation occurring from overserved neighbouring areas.

Overall, analyses have tended to be conducted using aggregated data, or a single deprivation statistic, which offer fewer opportunities to study patterns associated with smaller groups within society. Additionally, few studies have focused on the idea of neighbourhoods[31,33], with these studies tending to look at large clusters of neighbourhoods. For example, clusters of Census Tracts in Toronto were used to assess resources available to local residents, and how these might impact on oral health[33], while a stratified random sample of neighbourhoods, identified through postcodes, was selected to study the effects of neighbourhood disadvantage and self-reported oral health[31] in Adelaide, Australia.

While it is important to consider health outcomes at broader geographical or national levels, particularly because many policies are created at such levels[34], for some people neighbourhood environments may be a more important determinant of their health[35]. Therefore, the ability to study neighbourhoods may allow for a better understanding of small area differences in health, as well as to see why outcomes may differ between places, and which neighbourhood features may be causing these differences. The application of new methods could help to better understand theoretical pathways and causal mechanisms affecting health at the small area level, through which influential features in different types of places could be identified. Increased understanding of these theoretical mechanisms is a pursuit that could greatly benefit dental public health[36]. In the context of this review, knowledge of these underlying mechanisms, and differences in mechanisms between places, can add to our theoretical knowledge of the role of geography in dental public health, and allow for a more bespoke or considered approach to population level oral health in different locations. The next section outlines the first of the methods that may help with such analysis.

Spatial microsimulation modelling

Spatial microsimulation is a method for creating large-scale simulated population micro datasets[37]. This 'bottom-up' approach focuses on individuals or households, as opposed to 'top-down' methods which focus on aggregate statistics and flows. The inclusion of geographical data adds the 'spatial' element to the method, and allows for the creation of rich datasets at a variety of geographical scales. The method has its origins in aspatial microsimulation models, primarily developed by economists, and there is a long successful history of applications of national public policies[12] that have not analysed geographical differences. A rare example of this application within dental public health was a model investigating the effects of fee and insurance changes on dental attendance in the United States[38]. This remains one of the few uses of microsimulation in the oral health literature: however, due to its national level scale, as well as the lack of comparison of geographical areas, this would not necessarily be considered a 'spatial' microsimulation.

Guy Orcutt is considered the creator of the microsimulation technique[39], which was used to generate large-scale synthetic populations on which to analyse the impacts of population changes on policies (and vice versa). Since then, the method has been further developed within geographical studies, and it was in this field that the first geographical information about individuals was integrated into this framework, spawning the first 'spatial' microsimulation model[40].

The method works by combining Census data with national-level survey data. Census data provide counts of individuals or households with certain characteristics in geographical areas, while survey data hold records of individuals or households with additional associated data often not found in the Census (e.g. tooth brushing frequency). The modelling can be applied at numerous geographical scales, as well as small clusters of geographical areas, allowing for larger study areas to be built from these, or conversely for analyses of much smaller areas than would usually be available. The need for this approach arises due to the lack of publicly available population microdata. Where data are available, often only small numbers are disclosed for larger geographical areas due to issues of cost and confidentiality. National-level surveys, while technically a form of microdata, are often only available for large geographical areas. Spatial microsimulation presents an opportunity to overcome such data issues.

Previously, spatial microsimulation has been used in a number of health-related studies. Within the UK, examples include simulations of long-term illness, depression and anxiety in York[36] which were subsequently analysed using thematic mapping, as well as a study of smoking rates for output areas in Leeds in an investigation of the optimisation of 'stop smoking' services[41]. Further studies in Leeds include the creation of custom datasets of health-related variables for studying obesogenic environments[42]. Examples from beyond the UK include studies of depression rates in the Republic of Ireland[43], small area estimations of angina and diabetes prevalence for New South Wales, Australia[44], and a study of dietary patterns (including soda consumption) and obesity rates in high and low income areas of Rio de Janeiro, Brazil[45]. Within the field, there are a number of different types of spatial microsimulation models, with a number of papers providing an overview of these[12,46].

A visual demonstration of the spatial microsimulation method is provided in Figure 1. The combining of shared variables from the Census and survey data (which are available at household or individual level) is used to 'constrain' the data through either sampling or reweighting methods, to create one dataset containing all of the variables of interest. As can be seen in Figure 1, a set of variables (in a comparable data format) common to both the survey data (a) and the Census data (b) are selected, before being combined using the spatial microsimulation method. This results in the final dataset (c), the creation of a population of individuals, distributed among the geographical zones of the Census (i.e. the geographical zone they live in), while also retaining their individual-level attributes from the survey data; these could include variables such as tooth decay, brushing habits, and attendance rates. These variables are known as the 'target variable(s)', and are the outcomes of interest to the study, which were not previously available at any geographically disaggregated level (most surveys only collect data at broad regional levels). Essentially, this process has created a representative synthetic population of individuals for a given geographical area (or scale), complete with socio-economic, demographic, clinical and behavioural characteristics. Such data would allow for a better understanding of the spatial patterning of oral health, which previously would not have been possible.

INSERT FIGURE 1 HERE

Since these datasets are 'new' (although some authors argue the data is not 'new', but rather replicates of existing records[47]), or not available in this format previously, validation of the results forms a key process. This can be done by comparing the fit of sampled or reweighted survey data to Census population totals ('internal validation'), or comparing the data outputs to other existing datasets ('external validation'). External validation is not always possible, as the lack of datasets is often what necessitates the need for the method in the first place. More thorough discussions of validation methods–and the practical application of spatial microsimulation models–are provided elsewhere, including the excellent work of Lovelace and Dumont[47].

INSERT TABLE 1 HERE

Table 1 provides an example of what spatial microdata might look like. Columns 1 and 2 represent the individual ID of each person, as well as the geographical zone in which they reside. Columns 3-7 represent the types of socio-demographic population data available in the Census, while columns 8 and 9 represent the type of clinical and behavioural data found in surveys such as the Adult Dental Health Survey[48]. Such a combination is typically not available from other sources.

Advantages and limitations of spatial microsimulation modelling

The primary advantage of the method is the ability to create new, custom datasets using reliable population synthesis techniques from readily available secondary data sources. There are a number of rich survey data sources available internationally, including the Adult Dental Health Survey in the UK[48], the National Health and Nutrition Examination Survey (NHANES) in the USA[49], the Brazilian Oral Health Survey[50], and the upcoming National Study of Adult Oral Health 2017-18 in Australia[51]. The ability to combine the data from these surveys on behaviours, attitudes and oral health is a novel approach, but one that is still underutilised in health inequalities research in general. Additionally, spatial microsimulation is becoming more readily accessible than ever, due to attempts to make the process more efficient for new and existing users. For example, the 'rakeR' package has been scripted to make spatial microsimulation easier in languages such as R[52], while an interactive website ('simSALUD'), designed to be easy to use, and specifically aimed at non-programmers, has also been created[53].

As well as the specific applications of spatial microsimulation modelling discussed in the previous section, the synthetic individual-level data produced by the models has a number of more general applications and uses[54]. The first is small area estimation of variables so that policies can be applied more accurately in a spatial sense, which is similar to the work of Tomintz and colleagues in their assessment of 'stop smoking' services[41]. The second involves the projection of the characteristics of those in the dataset into future states, and assessing how these may change, similar to the work of Ballas and colleagues[37]. This could be used to assess future planning of service provision. Finally, the effects of current policies can be assessed, including where the greatest impacts may be, by modelling the effects of a given policy across numerous small areas.

Spatial microsimulation can be particularly useful when attempting to operationalise theoretical frameworks. Additional target variables can be added to the analysis to match relevant theoretical concepts in the framework, for which there is often a lack of real-world data. The creation of representative populations with a range of behaviours, socio-demographic indicators, attitudes and clinical outcomes could allow for a singular, rich dataset to be used for operationalising and testing theory. For example, if looking to hypothesise and test pathways related to the social determinants of health, it is important to include a mix of socio-economic, demographic and health-related data, with Table 1 already having demonstrated the types of data that can be combined. The investigation of neighbourhood environments would require a similar mix of variable types, with one previous example demonstrating the use of spatial microsimulation to populate a neighbourhood-based theoretical framework[55].

As such, spatial microsimulation can address areas where limited or no data are available, by synthesising new variables. Additionally, dental public health is a discipline where population studies often involve surveys, interviews and questionnaires, which take time and money to prepare, disseminate, and collate. While it could be argued that spatial microsimulation could not replicate the depth of qualitative data analysis on occasions, both cost and time savings could be made by using the method instead of a large-scale survey, to create synthetic populations with relevant characteristics that could be tallied alongside other covariates. This may help, in turn, to give a more detailed picture of individual and household patterns and differences.

The statistical nature of spatial microsimulation models can also be seen as a positive because, while not possessing the interactivity of more dynamic simulation techniques, these 'important statistical mechanisms…ensure the similarity of what it predicts and what is actually observed in the data'[56] (p.446). Additionally, microsimulation data can form the backbone of more dynamic simulation models, including agent-based models, providing them with an accurate, representative population of individuals to model interactions on. This will be discussed in more detail later in the paper. Finally, the ability to disaggregate data more easily, as well as being able to make more accurate inferences about individuals and groups helps to avoid issues associated with the ecological fallacy[57]. This occurs when assumptions are made about individual characteristics based on aggregated data.

It is also worth acknowledging the shortcomings of the method. While the models can help overcome data issues, they are still limited by the data available to them. This can affect the amount and type of available variables to constrain the data, as well as target variables that may be simulated. Methods such as data linkage[58] and statistical matching[59] may offer solutions to these problems, through combining various individual level datasets. Spatial microsimulation is also not suited for analysing long-term behavioural responses and reactions[60]. While dynamic spatial microsimulation models can simulate populations into the future, these are typically based on numerical projections (with very limited exceptions of models that attempt to probabilistically model dynamics at the micro-level[61]) that do not take into account interactions and feedback mechanisms, which are key features in understanding emerging patterns of human behaviour. This is a limitation in a field such as dentistry, where behaviours and attitudes will likely form an important part of the analysis.

Agent-based modelling

Agent-based models represent another ‘bottom-up’ approach, and are computer simulations of real world environments, or ‘computer representations of systems consisting of a collection of discrete microentities interacting and changing over discrete time steps that give rise to macrosystems’[62] (p.3). Thus, systems level patterns emerge from the sum of interacting behaviours and characteristics over time[63], rather than being predetermined. The capability to model interactions (and account for feedback mechanisms occurring from these) is key to attempting to mimic important features of human actions and behaviours. This interactive approach sets agent-based modelling apart from traditional statistical techniques such as regression, which often simplify complex interactions by estimating independent associations between variables, while controlling for other neighbourhood or individual-level variables[62]. Conversely, agent-based models attempt to model the ways in which people interact with each other and their environments, and the changes and adaptations that occur from these interactions[62]. Indeed, agent-based models have been identified as likely to be the most suitable tool for studying complex health inequalities[64].

Agent-based modelling developed from the cellular automata models of the 1970s, which were simple patch-based simulations, with Thomas Schelling’s famous segregation model representing the first attempt at modelling human and societal behaviour[65]. A key tenet of agent-based modelling is the simplification of behaviours in the system being studied, before running models to observe the emergent phenomena that occur from these. These behaviours are implemented through rules which guide the running of the model and are based on theory or patterns from datasets. Simplification is necessary due to the complexity of living systems, making them almost impossible to mirror exactly in simulations. The number of rules and details required would be far too computationally intensive, while interpreting model output would become significantly more difficult with every layer of additional detail.

Although there is no universal definition of what constitutes an agent, it has been stated that these entities must be: autonomous, and free to interact with other agents which informs decision making; heterogeneous, with their own unique attributes such as age, gender and occupations; and, finally, active, with a pro-active and goal-directed nature, reacting to and perceiving scenarios, while being interactive and communicative, mobile, adaptive and capable of learning, with bounded rationality[67]. Agent-based models have been used more often in the wider public health field, with examples of applications including an investigation of the effects of segregation on healthy food consumption[68], as well as socio-economic differences in walking patterns[69]. Influenza outbreaks[70] and spates of other infectious diseases[71] have also received attention, with the method's flexibility meaning that investigations into future disease prevention scenarios have been possible[70].

Despite still being rare within the field, agent-based models have great potential within dentistry[72]. There have been a number of applications within the oral health literature, with some of this work taking on a geographical dimension. One study combined agent-based models with a system dynamics model (a 'top-down' approach that considers the stocks and flows of a system using differential equations) in a model testing the influence of word of mouth on the spread of oral health habits in an elderly population in New York City. This model demonstrated that social interactions were key, as increased interaction led to increased care seeking and preventive screenings[11]. In a prototype model also using agent-based models, system dynamics and GIS in New York City, it was shown that social networks were important in influencing dental visits, with the number of visits being greater with greater degrees of social influence in the networks of agents. This in turn led to better oral health[73].

Another example of the application of GIS includes the work of Jin and colleagues[74], which similarly focused on the oral health of older people in northern Manhattan, New York, this time assessing the influence of social support on oral healthcare programme accessibility. The geographically explicit locations of senior centres were used to establish social networks in agents, while a variety of socially mediated transportation options (walking, car, subway, bus) were also incorporated (i.e. those with friends could share a car ride). The oral health screening centres the agent would visit were determined by their oral health status treatment needs, and social network ties. Social influence was found to exert a large effect on the activities and health behaviours of older adults, while the frequency of screening events and coverage of oral health programmes were both important determinants of improved oral health status.

This research followed previous work that also modelled the accessibility of screening and treatment to elderly patients in northern Manhattan[75]. Different transportation options followed geographically explicit routes (i.e. pavements for walking, roads for driving) in the model, while senior centres and community dental clinics were present as physical locations. Agents were also given a daily routine, individual characteristics and an experience history (of transport options), all of which could affect their interactions. Decisions were also influenced by social networks, while agents chose clinics based either on distance or the service provided. Once at the clinic, the choice of whether to participate in the screening programme was made, as well as whether to accept a referral for treatment. If treatment occurred, oral health improved. The study showed that proximity to screening and treatment facilities was important for health-seeking behaviours, while also demonstrating that social support can lead to transport assistance which, in turn, promotes health seeking behaviours. Participation in screening programmes positively affected oral health, through referrals for treatment.

Although the above studies were conducted on populations of only 500 and 100 respectively, they show the depth and complexity that can be incorporated into dental public health scenarios. Despite the above examples, it is important to remember that agent-based models are not necessarily geographic information systems, but become one when geographical data are added to the model. This has become easier due to the number of agent-based modelling platforms that are capable of handling spatial data. With the addition of such data come added concerns about the level of detail to include, and possible effects on the size and run time of models. The need for spatial data will depend on the study at hand, and sometimes a subset of the most important geographical features (e.g. roads or houses) may be preferable to including every detail of the area being studied.

There are a number of examples of non-spatial agent-based models within dental public health. These include an analysis of the demand for dental visits. The decision of agents to visit a dentist was determined by an individual's attention to their dental health, and whether they had been to the dentist recently. If individuals attended and had treatment, they would encourage others to attend. The analysis demonstrated that patterns associated with attendance had an oscillatory nature, and that the social structures in which individuals were embedded, as well as the number of effective connections within these structures, played a key role in influencing demand[76]. Additionally, studies of dental behaviours and associations with friendship networks have also been conducted[77]. Initial research conducted among schoolchildren using questionnaires, and the statistical analysis of the data, were used to inform behaviour patterns for the agent-based model. The subsequent analysis demonstrated that behaviours diffused through agents via their developed friendship networks, with agents who were closer in their social networks more likely to adopt similar oral health habits (specifically tooth brushing). The more popular agents within these networks were also shown to have better tooth brushing habits, which could encourage others to take up similar habits. This example also demonstrates that statistical approaches such as regression can complement agent-based modelling, and aid in the identification of relevant variables or parameter values.

Given the complexity of some models, verification and validation are key issues that should be addressed. Verification involves debugging code, verifying calculations, and ensuring theoretical concepts are correctly implemented[66]. Validation establishes whether models lead to realistic representations of real-world phenomena, and can involve the use of expert opinion to judge the validity of model behaviour or output ('face validity' or 'Turing tests'), or assessing the internal validity of models by comparing output from multiple stochastic runs using different random seeds to test for consistent results. Testing the effects of parameter sensitivity on model output, and comparing findings from parts of a model to other, existing, agent-based models (or 'docking') are additional approaches to validation[66]. Validation can be difficult to perform however, as different agent-based models do not always produce data in the same way.

Advantages and limitations of agent-based models

The principal advantage of agent-based models is the ability to include interactions and feedback mechanisms within research designs. These features are key to understanding social systems, particularly in a field such as dental public health. From a geographical perspective, the ability to accurately replicate small geographical areas through the incorporation of GIS (including numerous built, physical and social features) in a dynamic modelling environment offers the chance to better understand the interactions surrounding small area outcomes in health. Further to this, agent-based models offer the opportunity to test theoretical frameworks[55,78]. Through their flexible design, models can be configured with initial conditions which mimic or test certain scenarios, theories, or sequences of events which may be expected as part of a theory or pathway. This has been used before to test theories on walking patterns[69], as well as the role of the fundamental causes theory in influencing patterns of violent victimisation[79]. The influence of variables and parameters can also be varied in order to model other theories, or to test alterative conditions and scenarios. Of course, the implementation of the rules that guide agents and the model are based on theory or data analysis, and help shape the model to replicate these.

Agent-based models can also be used to test future scenarios. For example, if a model has been created that has been fully verified, calibrated and validated, it may be possible to run this model into the future in order to obtain patterns of data for future years. This would most likely be exploratory; however, this could also be useful in assessing the effects of various interventions or policies. As such, agent-based models may help in creating longitudinal data where it did not previously exist. This could be used to predict future trends, although this could also be used to assess differences between certain study points, with societal data between Census points being one example. Similar to spatial microsimulation, there is also the potential for agent-based models to help reduce costs associated with research. For example, recent trials in dentistry have been funded for sums of £1.3 million[80] and £2.9 million[81], for studies comparing the clinical efficacy and cost-effectiveness of fissure sealants and fluoride varnish in preventing caries[80], and an investigation of effective approaches to managing decay in children's teeth[81], respectively. Given the open source nature of many datasets, and even accounting for the cost of researchers and computing power, agent-based modelling approaches are likely to present substantial savings.

It is also worth acknowledging the limitations of the method. One concern involves the theoretical underpinning of these models, since without this, there is a risk that model output could simply be categorised as 'blue skies research' if not theoretically grounded with a relevant real-world problem or solution in mind. It is also important to consider whether a system has been built at the appropriate level of description for the problem at hand, which is often hard to judge, and can negatively affect computational intensity and model interpretation. Additionally, simulations of human systems may require the modelling of irrational behaviours and subjective choice, all of which are hard to quantify and calibrate, and can affect the interpretation of the findings. The appropriate interpretation of findings, as already referred to, can be more difficult with agent-based models in general, while issues also arise concerning the trade-off between including complex systems theory and also simplifying models for practical reasons. This issue has no easy answer, and often depends on the intentions of the study. Finally, agent-based models can be very sensitive to their initial configuration, as well as small changes in rules that govern interaction, reinforcing the need for sensitivity analysis.

Where to next?

There are a number of research areas that would benefit from the application of the methods reviewed in this paper. The sugar tax in the UK[82] is a highly relevant example for policy. Dynamic simulation platforms such as agent-based models offer the opportunity to explore the effects of such policies under varying hypothetical scenarios, and they add an interactive element that statistical models cannot always account for. Spatial microsimulation would also be useful in this scenario, as the ability to create a population of individuals (pre-sugar-tax) with associated sugar consumption and behaviours would be a rich tool for data analysis, as well as for the agents in an agent-based model.

Water fluoridation is another topic that stimulates debate within dental public health, as, despite the acknowledged benefits in the literature[83], applications of such schemes are far from universal. Without the use of dynamic simulation approaches such as agent-based modelling, exploring the possible effects of such a complicated intervention would be even more difficult. The individual-level focus of agent-based modelling also means that more accurate assertions about different societal groups could be made about the effects of such interventions.

Continued inequality in tooth decay within society[84] is another important theme that could be addressed. Similar to the ideas suggested in relation to water fluoridation, the ability to test numerous intervention scenarios, and their effects on different populations could be invaluable for policymakers. Attempts have already been made within dentistry to simulate such interventions[31]; however, these have taken a 'top-down' approach, thus not allowing for disaggregation of patterns. Conversely, other research within dentistry has already tested the effects of social links on participation in screening programmes[11,73-75], so the aforementioned interventions related to inequalities in tooth decay would seem a natural progression. Other broader or more abstract concepts (such as advertising) could also be considered as future themes for investigation (i.e. toothpaste advertising at bus-stops), while the concept of social capital would be an ideal choice for agent-based modelling, given the ability to focus on relationships and interactions among individuals that are so important for this concept[85].

Moreover, despite their strengths, each method could be improved upon by using attributes of the other. Spatial microsimulation, for example, would benefit from the inclusion of an interactive element to the modelling of its populations, while agent-based models can be made more representative with the inclusion of accurate population microdata. Indeed, these two bottom-up methods are complementary, and address some of the limitations of the other[55,86]. Spatial microsimulation models are able to process large-scale data through list processing power, and provide numerical methods of reweighting population data, while agent-based models include interactions and behaviours, not being restricted by statistical approaches. This partnership has been used only once before within dental public health research[55]. This research aimed to test neighbourhood determinants of tooth decay, and used a spatial microsimulation model to supply population data for an agent-based model, before this combination was used to test a place-based theoretical framework in different geographical areas. The findings pointed to the importance of shops and sugar consumption in influencing decay levels.

Previous geographical research has employed this approach for studying student migration patterns in Leeds[56], demonstrating that a combined model utilising the two methods was able to model migration patterns more accurately than a microsimulation model on its own. Additionally, this combination has been used to investigate mortality data in the same city[87], which demonstrated the importance of personal histories in influencing these patterns. An individual's previous place of residence influenced their health regardless of their current residence. The authors commented that agent-based models can 'compliment MSM [microsimulation] by retrieving personal histories with great ease' (p.356). Further research has shown how personal attribute data on agents, derived from a microsimulation model, can be used to generate school, work and commuting interactions which can be coded into models[88]. Clearly, combining the two techniques presents a considerable array of opportunities.

Conclusions

This review has summarised two underutilised methods that could have a considerable impact on geographical studies of oral health. Both have great potential as stand-alone methods, and can help address some of the limitations of the other when combined. The open source nature of the research underpinning these methods and associated data makes them a particularly appealing prospect. These exciting methods offer researchers within dental public health the opportunity to study geographical variations in oral health in a level of detail previously not available, as well as presenting the opportunity to study complex systems-science-based health scenarios[89]. Examples in this review included sugar taxes, water fluoridation trials, and caries interventions, to name but a few of the topics to which these methods could be applied within dental public health.

The inclusion of interactive agents, and associated feedback mechanisms, is essential in attempting to mimic real-world scenarios as closely as possible, while a focus on individual agents allows for more accurate inferences to be made about populations, also allowing for system-level models to be built from the bottom up. Perhaps most importantly, these methods can add to our understanding of the importance of theoretical concepts. The flexible nature of agent-based models and spatial microsimulation allows for the testing of numerous scenarios on a population with a vast array of associated and relevant variables[55]. Testing relevant theories in complex, multifactorial systems is vital if we are to increase our understanding of the relevance of geography (and other social sciences) to oral health. This is a step the field must take if we are to better understand the complexity associated with key topics in oral health, and in the discipline and practice of dental public health.

Acknowledgements. This research was funded by a Medical Humanities Sheffield studentship from the University of Sheffield, as well as the 2016 Professor David Locker Research Scholarship.

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Fig. 1 – Visual representation of the spatial microsimulation process

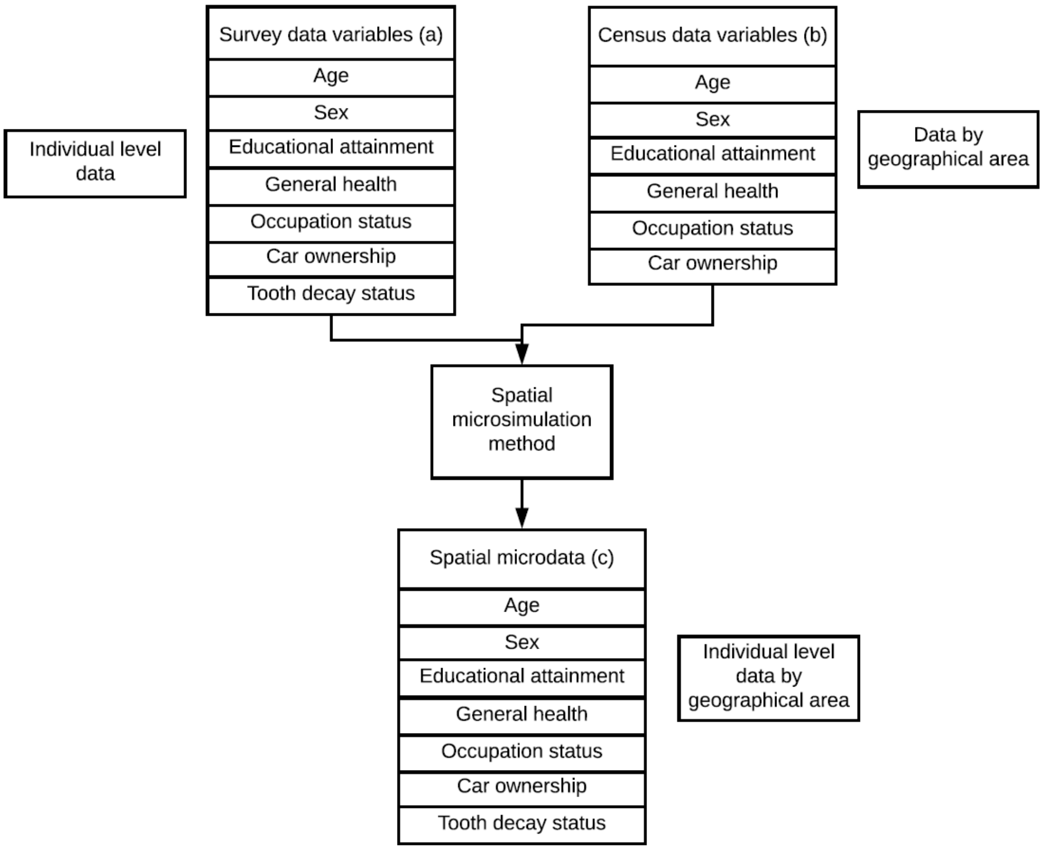

Table 1 – Hypothetical Spatial Microsimulation dataset

ID (1)	Zone (2)	Sex (3)	Age (4)	General Health (5)	Car ownership (6)	Education level (7)	Decayed teeth (8)	Brushing frequency (9)
1	1	Female	65	Bad	Yes	Degree	0	Twice daily
2	1	Male	53	Bad	Yes	Other qual	6	Once daily
3	1	Male	71	Good	Yes	Other qual	2	Once daily
4	1	Female	85	Fair	No	Other qual	1	Twice daily
5	1	Male	36	Very good	Yes	Degree	0	Twice daily