Paper presented at the International Seminar on Transport Knowledge and Planning Practice at the University of Amsterdam, 14-16 October 2009. Published in *Transport Reviews* 31 (2011), 2, 161-177.

From Macro to Micro – How Much Micro is too Much?

Michael Wegener
Spiekermann & Wegener (S&W)
Urban and Regional Research
Dortmund, Germany
E-mail: mw@spiekermann-wegener.de

Abstract. This paper discusses the usefulness of the trend towards microsimulation in urban transport and land use modelling for the planning practice. It starts with a history of urban transport and land use models and observes a trend towards increasing conceptual, spatial and temporal resolution stimulated by improved data availability, higher computer speed and better theories about mobility and location individual behaviour. While recognising these advances, the paper calls attention to the problems of disaggregate models in terms of data requirements, computing time and stochastic variation and shows that in the light of new challenges cities are facing, such as energy scarcity and climate change, not further refinement but more focus on basic needs and constraints is needed to make the models useful for the planning practice. As a possible solution to the macro-micro debate it calls for a theory of multi-level models according to which for each planning task there is an appropriate level of conceptual, spatial and temporal resolution. The paper closes with an example of a multi-level land use, transport and environment model ranging from the European to the grid-cell level.

Introduction

It is common wisdom among planners that the locations of human activities, such as living, working, shopping, education or leisure, determine the spatial interactions or trips in the transport system – this is the basic rationale of traffic models. The reverse relationship, that the opportunities for spatial interactions provided by the transport system co-determine the location decisions of developers, firms and households, is less well known. Attempts to model the two-way interaction between urban transport and land use started in the USA in the 1960s and spread from there to other countries. Today there exist a broad range of integrated urban land-use transport models world-wide. New developments in model theory and method, such as activity- and agent-based models, in which the behaviour of individual persons, households or firms are modelled, have widened the range of issues that can be studied.

The mainstream trend in urban transport and land use modelling is disaggregation. With refined travel surveying techniques, activity-based travel models have become the state of the art, and with increased availability of high-resolution grid cell or parcel information microscopic agent-based land use models are proliferating. There are persuasive reasons for this trend: With growing individualisation of society, urban life styles and hence mobility and location patterns and social networks are becoming more diversified, and disaggregate models are better able to capture this heterogeneity. In addition, new model extensions addressing environmental issues, such as air quality, noise, landscape and water require high-resolution grid cell models.

However, only very few microscopic urban travel and land use models have become operational. There are practical reasons for this: the data requirements and computing times of these models tend to be enormous. However, there are also fundamental conceptual problems with disaggregate models. Disaggregate transport models are too slow to be executed several times in integrated land-use transport models and to allow the examination of the large number of scenarios required for the composition of integrated strategies or policy packages. The results of microsimulations are subject to stochastic variation, i.e. may vary significantly between model runs with different random number seeds unless averaged to a level of aggregation they were designed to overcome. If, as most experts agree, the imperative of reducing greenhouse gas emissions and the ultimate depletion of fossil fuels will make transport significantly more expensive in the future, mobility and location will depend less on individual life styles and preferences and more on basic needs and constraints. This will change the priorities in transport and land use modelling and weaken the reasons for using activity-based or agent-based models.

The conclusion is that disaggregation has a price and that the principle "the more micro the better" may be misleading. This suggests that for each modelling task there is an appropriate level of conceptual, spatial and temporal resolution. The challenge is to develop a theory of balanced multi-level models which are as complex as necessary and, to quote Albert Einstein (1934), as simple as possible but no simpler. The paper closes with an example of a multi-level land use, transport and environment model ranging in spatial resolution from the European region to the grid-cell level.

History of urban transport and land use modelling

The growing knowledge about the relationships between urban land use and transport was behind the development of the first integrated land-use transport models in the USA in the 1960s. (Wegener, 1994). The *Model of Metropolis* by Lowry (1964) was the first attempt to quantify the land-use transport feedback cycle in one integrated model. The Lowry model stimulated a large number of increasingly complex land-use transport models in the USA, including the models by Goldner (1971) and Putman (1983, 1991), and only little later also in Europe, such as the models by Echenique (Geraldes *et al.*, 1978), Mackett (1983) and Wegener (1982).

Many of these early models were not successful because of unexpected difficulties of data collection and calibration and the still imperfect computer technology of the time. More important, however, was that the models were mainly used to improve the efficiency of the transport system under conditions of urban growth and had nothing to say about the ethnic and social conflicts arising in US cities at that time. Moreover, the models were committed to the paradigm of top-down synoptic rationalism in planning theory, which was increasingly replaced by incremental, participatory forms of planning. In his "Requiem for large-scale models", Lee (1973) accused the models of "seven sins": hypercomprehensiveness, grossness, mechanicalness, expensiveness, hungriness, wrongheadedness and complicatedness. The result of the change in acceptance of the models was that the urban modelling community largely retreated to academia.

But the requiem was premature. Many of the technical problems of the early models were solved by better data availability and faster computers. The spatial and substantial resolution of the models was increased and they were based on better theories, such as bid-rent theory, discrete choice theory and user equilibrium in transport networks. In addition better visualisation techniques made the results of the models better understood by citizens and policy makers.

The 1990s brought a revival in the development of urban land-use transport models. New environmental legislation in the US, such as the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 required that cities applying for Federal funds for transport investments demonstrate the likely impacts of their projects on land use and the environment. In Europe the European Commission initiated a large research programme in which in several projects integrated land-use transport models were applied (Marshall and Banister, 2007). Several integrated land-use transport models, such as MEPLAN (Echenique *et al.*, 1990), TRANUS (de la Barra, 1989), DELTA (Simmonds, 1999) and UrbanSim (Waddell, 2002) were applied in a growing number of metropolitan areas, and the first such models, TRANUS and UrbanSim, were made available as Open Source on the Internet.

More recent developments seem to herald an unlimited golden future for urban land-use transport models (Wegener, 2004). New developments in data availability brought about by geographical information systems (GIS) and further advances in computer technology have removed former technical barriers. New developments in model theory and method, such as activity- and agent-based models, have widened the range of issues that can be studied. A world-wide community of urban modellers meets regularly at conferences, such as the World Conference on Transport Research (WCTR), Computers in Urban Planning and Urban Management (CUPUM) and the Annual Meeting of the Transportation Research Board (TRB).

Disaggregate urban transport and land use models

Any observer of professional journals will agree that the main current trend in urban transport and land use modelling is disaggregation. There are both technical and conceptual reasons for this. Technical reasons include refined travel surveying techniques and increased availability of high-resolution grid-cell or parcel information from geographic information systems as well as huge advances in computer capacity and speed. Conceptual reasons include improved theories and empirical knowledge about human cognition, preferences, behaviour under uncertainty and constraints and interactions between individuals in households, groups and larger social networks. Stimulated by these advances, activity-based microsimulation travel models have become the state of the art and microscopic agent-based microsimulation land use models are proliferating.

There are persuasive reasons for this trend towards disaggregate models. In affluent and highly mobile societies there has been a growing potential for individualisation, the choice of diversified life styles and social networks and hence mobility and location patterns (Salomon et al., 2002). Disaggregate models of individual behaviour are better able to capture this heterogeneity. In addition, new model extensions addressing environmental issues, such as air quality, noise, landscape and water require high-resolution grid cell models.

The micro-macro dichotomy, i.e. the relationship between individual behaviour and social processes, has been a recurrent theme in the social sciences (Schelling, 1978, Alexander *et al.*, 1987). Microsimulation was first used in the social sciences by Orcutt *et al.* (1961). Early applications with a spatial dimension covered a wide range of processes, such as spatial diffusion (Hägerstrand, 1968), urban development (Chapin and Weiss, 1968), travel behaviour (Lenntorp, 1976, Poeck and Zumkeller, 1976, Kreibich, 1979), household dynamics (Clarke *et al.*, 1980, Clarke and Holm, 1987) and housing choice (Kain and Apgar, 1985, Wegener, 1985). Since the 1980s several microsimulation models of urban land use and transport have been developed (Hayashi and Tomita 1989, Mackett, 1985, 1990, Landis, 1994, Landis and Zhang, 1998a, 1998b, Waddell, 1998a, 1998b, 2002, Wegener and Spiekermann, 1996, Salomon *et al.*, 2002, Miller and Salvini, 2001, Beckmann *et al.*, 2007, Ettema *et al.*, 2007, Feldman *et al.*, 2007b).

An alternative modelling approach originated from the theory of cellular dynamics. Cellular automata (CA) are objects associated with rectangular areas called cells. CA follow simple stimulus-response rules to change or not to change the state of cells based on the state of adjacent or near-by cells (White and Engelen, 1994, Batty and Xie, 1994, Batty, 1997, 2005). More complex stimulus-response behaviour is possible in multi-reactive agent or agent-based models. Multi-reactive agents are automata with the ability to change their environment but also their own behaviour, i.e. they are able to learn (Ferrand, 2000).

The most advanced type of spatial microsimulation models are activity-based travel models. Disaggregate travel models aim at a one-to-one reproduction of spatial behaviour by which individuals choose between mobility options in their pursuit of activities during a day (Axhausen and Gärling, 1992, Ben Akiva *et al.*, 1996). Activity-based travel models start from interdependent activity programmes of household members and translate these into tours consisting of one or more trips. Activity-based travel models disaggregate travel behaviour by time of day, which permits the modelling of choice of departure time. There are also disaggregate traffic assignment models based on queuing or CA approaches, e.g. in the TRANSIMS (Nagel *et al.*, 1999, TRANSIMS, 2009) and MATSim (Balmer *et al.*, 2008) projects, which reproduce the movement of vehicles in the road network with a level of detail not known before.

However, not all disaggregate urban and transport modelling projects have been successful (see, for instance, Wagner and Wegener, 2007, Nguyen-Luong, 2008). Many large modelling projects failed to deliver in the time available or had to reduce their too ambitious targets. Many applications of established models by others than their authors did not become operational. Many projects got lost in data collection and calibration and did not reach the state of policy analysis. Many projects remained in the academic environment and produced only PhD theses. Many applications of microscopic activity- or agent-based models ignored the pitfalls of stochastic variation and published results with illusionary precision. In addition, most present modelling projects have not yet responded to the new challenges urban planning will face in the future. It will take some time until the first urban land-use transport models fully based on microsimulation will be operational and be adopted by the planning practice.

Problems of disaggregate models

The reasons for these failures are partly practical, such as large data requirements and long computing times, and partly conceptual, such as uncertainty due to stochastic variation. In addition the new challenges cities are facing may call for other priorities in model design.

Data requirements

Disaggregate spatial microsimulation models require disaggregate data for a calibration period. Activity-based travel models and agent-based land use models require detailed information on the socio-economic situation of individual households and age, gender and occupation of each household member. In most countries this kind of information is not available from census data, either for privacy reasons or because full censuses tend to be less frequently taken in many countries. Except for work trips, mobility behaviour with the detail required for activity-based travel models can be obtained only from extensive surveys or travel diaries, which are time-consuming and location-specific, i.e. cannot be easily transferred to other regions. Recent suggestions to use data on the movements of mobile phone users routinely collected by phone companies give rise to substantial privacy concerns and meet with heavy resistance by civil rights groups.

Because of these constraints in data availability, the usual practice is to construct "synthetic populations" of households and firms from more aggregate data based on statistical estimation techniques, such as Monte Carlo sampling or iterative proportional fitting (Beckman *et al.*, 1995). These techniques ensure that the synthetic micro data are consistent with known aggregate marginal distributions, but they also add a rarely addressed level of uncertainty to the models.

On the positive side, detailed land use data are increasingly available from high-resolution GIS databases, which allow spatial disaggregation down to the parcel or grid cell level and geocoding of micro locations of households and trip destinations. Similarly, the coding of street networks has become easier by detailed GIS network databases.

Computing time

The computing time for existing microsimulation models is measured in terms of weeks or days, not hours. Experience has shown that advances in computing speed have not led to shorter run times but to more sophisticated and hence more computation-intensive models. In particular activity-based travel models with their travel demand, shortest paths and assignment consume the most computing time (Wagner and Wegener, 2007). The situation gets worse in integrated land-use transport models in which the travel model has to be run several times for different years of the simulation, even if computing time is saved by starting from travel times and travel costs of the loaded network at the end of the previous period, or by running the travel model only every few simulation periods.

The long computing times have serious implications for calibration and application of the models. If in the calibration phase only few test runs of a model are possible, this reduces the number of sensitivity tests to check the plausibility of model behaviour. In the application phase microsimulation models are too slow to allow the examination of the large number of scenarios required for the identification of the best composition of integrated strategies or policy packages.

Stochastic variation

In addition, there are serious conceptual problems of stability of microsimulation models due to stochastic variation. Stochastic variation, also called microsimulation or Monte Carlo error, is the variation in model results between simulation runs with different random number seeds.

The magnitude of stochastic variation is a function of the number of choices and the number of alternatives simulated. It is largest when a small number of agents chooses between a large number of alternatives, and it is smallest when the number of choices is large and the choice set is small. This is illustrated in Figure 1. The figure shows the results of the simulation of 10,000 (left) and 1,000 (right) choices (C) by agents, such as individuals or households, between 100 (top), 400 (centre) and 900 (bottom) alternatives (A), such as destinations or residential locations on a square grid of cells. In this demonstration example all locations are equally attractive, so the ideal allocation would be a flat distribution equal to the average number of choices per cell. The six surfaces show the variation of choices from that ideal distribution in the form of the standard deviation (SD) or average deviation from the mean of a representative simulation run; the surfaces would be different but similar for simulation runs with different random seeds.

It can be seen that the deviations due to stochastic noise quickly become larger if the number of agents becomes smaller or the number of alternatives becomes larger even in terms of standard deviation – the deviations of individual choices from the mean may be a multiple of the standard deviation. Whether this is acceptable depends on the purpose of the application. If the model is used primarily as a didactic tool to improve the understanding of the mechanisms of urban development, a deviation of, say, ten percent may be acceptable. If, however, the model is to support the choice between only marginally different planning alternatives, even a deviation of a few percent may make it impossible to reliably identify the best alternative.

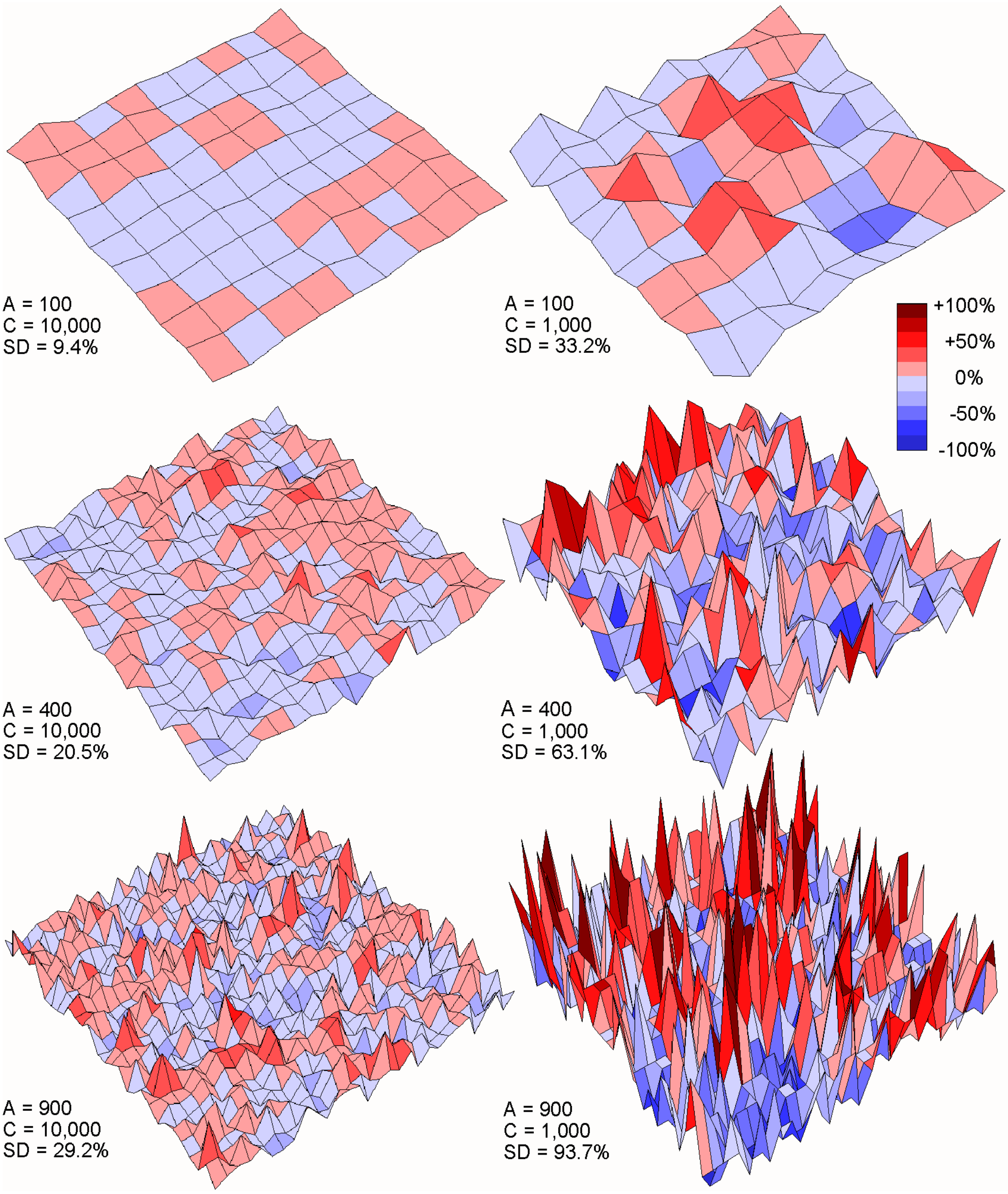

Figure 1. Stochastic variation expressed as standard deviation (SD) of different combinations of number of choices (C) and number of alternatives (A)

In most applications the number of agents (or choices) may be larger than in the demonstration examples of Figure 1, but so may be the number of alternatives. Therefore a larger range of combinations of numbers of choices and alternatives was tested. Figure 2 shows that, with some random noise, stochastic variation expressed as standard deviation from the ideal values is a function of the ratio of choices and alternatives or the average number of choices per alternative. If the stochastic noise is to be less than one percent, there must be 10,000 times as many choices as alternatives. Similar results were obtained when the alternatives differed in attractiveness and choices were made by logit discrete choice, unless very high beta values practically precluded any choice.

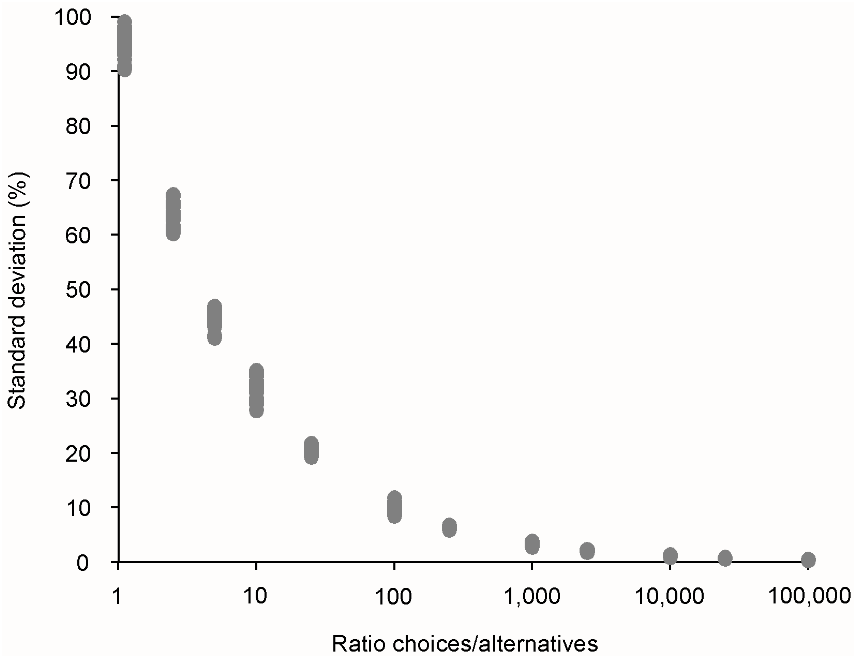

Figure 2. Stochastic variation as a function of choices and alternatives

These results are consistent with those of Moeckel (2007) who analysed the effects of stochastic variation in a microsimulation model of firm location. He ran the model fifteen times over 30 years with different random number seeds. When aggregated to five subregions, the rates of change of population differed by only a few percent, whereas the rates of change of employment varied by up to more than 100 percent or even changed in sign. The reason was that the microsimulation model processed 1.2 million households but only 80,000 firms. After similar tests with the microsimulation household location model SimDELTA, Feldman *et al.* (2007a) concluded that random variation resulting from the Monte Carlo simulation are overwhelming the systematic variations resulting from changes to the model inputs, and that even controlling the way in which random numbers are supplied to the model will not remove the need to carry out multiple runs. Also Ševcíková *et al.* (2007), running similar tests with UrbanSim yet using a different method, concluded that multiple runs are required to arrive at robust results. Veldhuisen *et al.* (2000), however, reported that in the activity-based travel model RAMBLAS the influence of Monte Carlo error on the aggregate results was negligible.

There are four methodological alternatives to deal with the problem of stochastic variation of microsimulation models:

- One way is to aggregate the results of microsimulation models to a higher level, i.e. from raster cells to zones, or from smaller to larger categories of households or firms. However, this defeats one of the main motivations for microsimulation, to get a more detailed picture and to overcome aggregation error.

- Another way is to artificially increase the number of choices simulated. This was done by Hunt *et al.* (2008) in their parcel-level simulation of developer actions in Baltimore. When calibrating the model they noted that the model missed the calibration targets for less-frequent land use transitions by up to a factor of five. They were able to reduce this deviation significantly by subdividing large parcels into smaller "pseudo-parcels" of 20x20 m size and aggregating the results to the original parcels thus increasing the number of choices simulated.

- A third, and most often recommended, way to overcome the problems of stochastic variation of microsimulation models is to run the models several times with different random seeds and to average over the results of the different runs. The question is then what is the minimum number of runs required to come close enough to the true value of a certain result of interest. Castiglione *et al.* (2003) ran the San Francisco activity-based microsimulation travel model 100 times each with different random number seeds and found that the variability of the model results depended on the type of model (vehicle availability, tour generation, destination choice, mode choice) and the level of geographical detail (travel analysis zone, neighbourhood, county). They concluded that for county-wide results in general only one run may be sufficient but that at the TAZ level the minimum and maximum value for an individual run could be as much as 10% to 25% different from the mean of the 100 runs. The California Department of Transportation and the U.S. Federal Highway Administration, in their guidelines for applying traffic microsimulation modelling software (Dowling *et al.*, 2002, Federal Highway Administration, 2004), advise how to calculate the necessary number of simulation runs for distinguishing between policy alternatives with a desired level of confidence. Depending on the minimum difference between the results of interest of the two alternatives to consider them different with a desired level of confidence, between four and 65 runs are required. If the minimum difference between the two alternatives is to be with 95% probability smaller than their standard deviation, twelve runs are needed.

- A fourth method is to explicitly recognise the stochastic nature of the results of microsimulation models and present them as such. This is particularly relevant for agent-based land use models such as the Environment Explorer which predicts land use transitions of grid cells by discrete land use categories (Engelen *et al*., 2003). In a recent application to the Netherlands the results were presented not as deterministic forecasts but as probabilities of development derived from multiple simulation runs (de Nijs, 2009). The question remains to what degree such probabilistic forecasts support the choice between different planning alternatives.

Given the already very long computation times of microsimulation transport and land use models, the need for multiple runs seems to be a serious impediment to their application in the planning practice. This may explain why many microsimulation projects have largely ignored the issue of stochastic variation and presented results with illusionary precision, such as high-resolution grid cell maps of projected land use distributions without reference to their stochastic nature.

New challenges

Beyond these technical difficulties, urban transport and land use models are facing new challenges that will have significant consequences for the questions to be answered by urban transport and land use models and hence for their design. Most experts agree that in the future the need to reduce greenhouse gas emissions and energy scarcity will make transport significantly more expensive. How will this affect mobility and location behaviour? Will distances travelled to workplaces, shops, services and leisure become shorter? Will activities at distant locations be given up or be replaced by telecommunication and so reduce the number of trips? Will there be a renaissance of public transport, walking and cycling? Will suburbanisation be halted or even reversed? Will greenfield shopping centres be abandoned for local shops? What will be the impacts on equity? Will there be a social divide between those who can maintain their mobility and those who must give up their cars?

Many present transport and land use models are unable to answer such questions. Many travel models used in the planning practice cannot model the impacts of significant energy price increases either because they do not consider travel cost in their trip distribution or modal split models of, if they do, work with elasticities estimated in times of cheap energy and so are likely to underestimate the impacts of higher transport costs. Many models assume fixed trip rates and so are unable to predict induced or suppressed travel demand due to travel cost changes. Only very few travel models (e.g. Arentze *et al.*, 2008, Ettema *et al.*, 2009) relate travel costs to household budgets for housing, transport and other expenditures, although these represent ultimate constraints on car ownership and mobility in case of significant travel cost increases. Many travel models do not model car ownership as a function of household travel budgets.

Many transport and land use models are also unable to forecast the impacts of future urban policy responses to climate change and energy scarcity, such as carbon taxes and emission trading, enforcement of anti-sprawl legislation, redirection of transport investment to public transport and transport demand management through road pricing or parking fees or promotion of alternative vehicles or fuels, or policies to cope with new types of social conflict, such as compensation of groups/communities most affected by transport cost increases and the provision of minimum standards of access to basic services and participation in social and cultural life, in particular in low-density suburban and rural areas.

What will be the implications of higher travel costs for the macro-micro debate? If mobility becomes more expensive, urban location and mobility decisions will depend less on individual life styles and preferences but more on basic needs and constraints. Individual life styles will become less diversified and mobility and location behaviour less heterogeneous. If the ranges of options to choose from are constrained by powerful restrictions, choice sets will become smaller and choices more predictable. This will make forecasting easier. Bit it will also weaken the reasons for applying microscopic activity-based or agent-based models.

How much micro is enough?

Despite these problems, microsimulation modellers today engage in ever more ambitious plans to further raise the complexity and spatial resolution of their models. The common belief among most microsimulation modellers seems to be: the more micro the better. This is the dream of the one-to-one Spitfire:

> "Simplifying assumptions are not an excrescence on model-building; they are its essence. Lewis Carroll once remarked that a map on the scale of one-to-one would serve no purpose. And the philosopher of science Russell Hanson noted that if you progressed from a five-inch balsa wood model of a Spitfire air plane to a 15-inch model without moving parts, to a half-scale model, to a full-size entirely accurate one, you would end up not with a model of a Spitfire but with a Spitfire."
>
> Robert M. Solow (1973, 276)

There seems to be little consideration of the benefits and costs of microsimulation: Where is microsimulation really needed? What is the price for microsimulation? Would a more aggregate model do? For spatial planning models, the answer to these questions depends on the planning task at hand. For instance, for modelling the impacts of transport on land use, much simpler travel models are sufficient to calculate the travel times and travel costs or accessibility indicators used in the land use allocation models.

The conclusion is that under constraints of data collection, computing time and stochastic variation there is for each planning problem an optimum level of conceptual, spatial and temporal model resolution. That optimum is a resolution sufficiently detailed for the planning task at hand and at the same time sufficiently robust, i.e. not distorted by natural randomness or stochastic variation. However, there has been only little research on how much detail and how much robustness of urban models is required. This suggests to work towards a theory of balanced multi-level urban models which are as complex as necessary and, to quote Albert Einstein (1934), as simple as possible but no simpler. Future urban models will be modular and multi-level in scope, space and time.

Multi-level modelling: the Dortmund example

As an example of a multi-level urban model the multi-level model system developed at the Institute of Spatial Planning of the University of Dortmund and applied in many European and national projects, such as PROPOLIS (Lautso *et al.*, 2004) and STEPs (Fiorello *et al.*, 2006), will be briefly presented. After its experience with the full-scale microsimulation urban transport and land use model ILUMASS (Beckmann *et al.*, 2007), the project team concluded that because of the problems of data requirements, long computing times and stochastic variation discussed above, full-scale microsimulation urban transport and land use models are not a viable alternative for practical policy applications in the foreseeable future (Wagner and Wegener, 2007).

The model system consists of three spatial levels (Figure 3). The top level is the European level with 1,330 NUTS3 or equivalent regions in the European Union plus Norway, Switzerland and the West Balkan countries. The medium level is the urban region of Dortmund with 246 internal and 54 external zones. The lower level is the urban region subdivided into 209,000 grid cells of 100x100 m size. The relationship between the European and urban levels is called multi-level because the urban region is only a small part of Europe. The relationship between the zonal and grid-cell levels is called multi-scale as they differ only in spatial resolution.

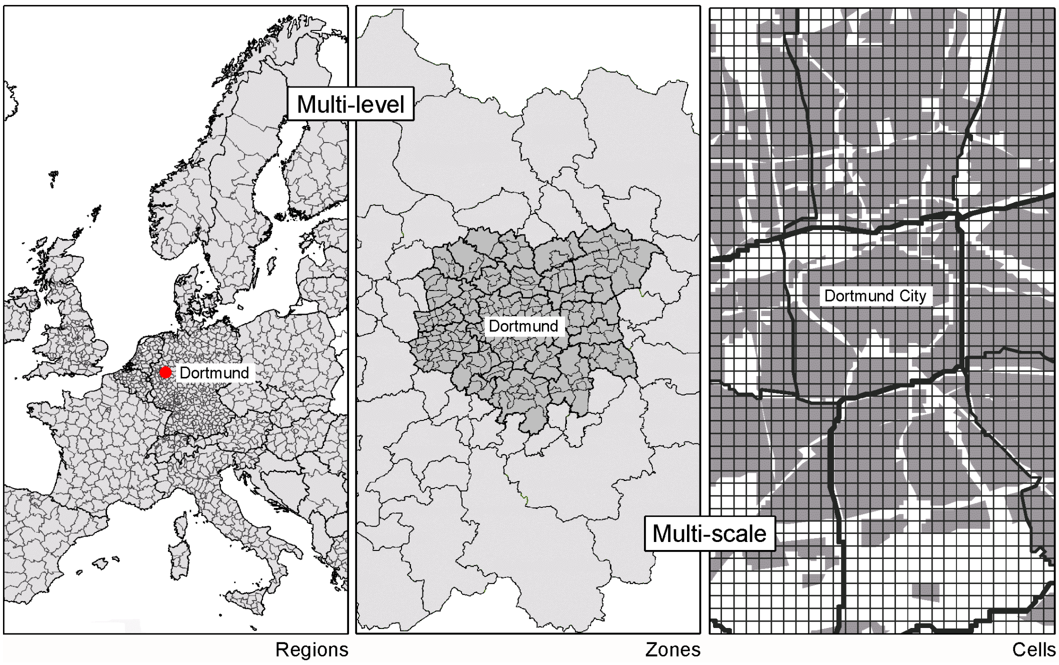

Figure 3. The multi-level model system of the Dortmund urban region

At the European level the regional economic model SASI developed together with the Technical University of Vienna (Wegener and Bökemann, 1998, Wegener, 2008) is applied. The SASI model is a recursive simulation model of socio-economic development of regions in Europe subject to exogenous assumptions about the economic and demographic development of the European Union as a whole and transport infrastructure investments and other transport policies. It differs from other regional economic models by modelling not only production (the demand side of regional labour markets) but also population (the supply side of regional labour markets). The SASI model has six forecasting submodels: (1) European developments, (2) regional accessibility, (3) regional gross domestic product, (4) regional employment, (5) regional population and (6) regional labour force. The model predicts for each year until 2030 for each region production and employment by economic sector, population, labour force and migration and attractiveness indicators, such as multimodal accessibility.

At the medium or zonal level the urban land-use transport model developed at the Institute of Spatial Planning of the University of Dortmund (IRPUD) is applied (Wegener, 2001). The IRPUD model has a modular structure and consists of six submodels operating in a recursive fashion on a common spatio-temporal database: (1) transport, (2) ageing, (3) public programmes, (4) private construction, (5) labour market and (6) housing market. The model predicts for each simulation period intraregional location decisions of industry, residential developers and households, the resulting migration and travel patterns, construction activity and land use and the impacts of public policies in the fields of industrial development, housing, public facilities and transport.

At the lowest or cell level, the Raster model developed in the PROPOLIS project (Spiekermann, 2003) calculates indicators for which a disaggregate treatment of space is required. In particular emission-exposure algorithms such as air dispersion, noise propagation, but also land coverage, landscape fragmentation and the exposure of population to pollutants and noise, require a higher spatial resolution than zones. The Raster model calculates emission indicators at source, such as CO_2, NO_x, particular matter (PM) or noise, and exposure indicators at destination, such as air quality or noise intrusion by affected population group as well as quality of life indicators, such as access to and fragmentation of open space.

Ideally, feedback between the three model levels should be both top down and bottom up. To date, only top-down effects have been implemented. The results of the SASI model serve as regional control totals for the IRPUD model, and the results of the IRPUD model are passed on to the Raster model for calculating environmental indicators. To implement feedback in the reverse direction, from cells to zones and from zones to regions in one integrated multi-level model, remains a challenge for future research (Spiekermann and Wegener, 2008).

The rationale behind the three-level organisation of the model system is that each modelled process is modelled at the appropriate spatial resolution. As noted above, the optimum spatial resolution is sufficiently detailed for the planning task at hand and at the same time sufficiently robust, i.e. not distorted by randomness or stochastic variation. This implies for the three model levels:

(1) *Regions.* At the European scale regional economic development depends on location factors, such as economic structure, availability of skilled labour and business services and accessibility in Europe. Long-distance migration depends on job opportunities and legal, cultural and language barriers. All these variables can be measured at the regional scale..

(2) *Zones.* At the intraregional scale local attributes become important. Location decisions of firms within a region depend on available land and accessibility to clients and important transport nodes, such as motorway exits and airports. Intraregional moves of households depend on housing supply, accessibility to workplaces and services and quality of life. In all these cases the relevant spatial units are neighbourhoods, not parcels or grid cells.

(3) *Grid cells.* Only environmental impacts, such as air dispersion and noise propagation, require a higher spatial resolution.

The model system described may not yet fully meet all requirements of the ideal multi-level model but is a move in that direction. The experience with the model system has shown that models with the appropriate level of disaggregation above the microscopic level are sufficient to give meaningful answers to contemporary questions of spatial planning with manageable data requirements and computing times, strong theoretical foundations and policy-relevant results – even for a future that will be very different from today.

Conclusions

The overall conclusion is that disaggregation has a price and that the principle "the more micro the better" may be misleading.

There are many good reasons to investigate human behaviour at the level of the individual to better understand the increasing diversity and heterogeneity of individual lifestyles, motivations, adaptation and learning and the complex patterns of social interactions and networks. This justifies microsimulation models as research tools, but for practical planning tasks they are no viable alternative to more aggregate models in the foreseeable future. There are practical limits to microsimulation, such as high costs of data acquisition and long computing times. There are ethical limits to collect detailed information about individual behaviour only for research. There are theoretical limits of calibration and validation of microsimulation models due to the stochastic variation of their results. These problems will be become more relevant as new challenges cities are facing, such as energy scarcity and climate change, will force modellers to focus more on basic needs and constraints and less on observed behaviour in times of cheap energy.

If urban modellers want to make relevant contributions to the solution of urgent contemporary problems of spatial planning, such as the necessary responses to climate change and energy scarcity, they will have to re-orient their attention from the diversity of individual life styles and preferences to the down-to-earth conditions of basic needs and constraints. Only then will they be able to competently and credibly inform the public about the risks of business-as-usual politics and what needs to be done to cope with the challenges of the future. The future of urban transport and land use modelling is therefore not refinement and detail but the identification of the appropriate level of conceptual, spatial and temporal resolution. The challenge is to develop a theory of balanced multi-level models which are as simple as possible but no simpler.

References

Alexander, J.C., Giesen, B., Münch, R. and Smelser, N.J. (Eds.) (1987) *The Micro-Macro Link* (Berkeley/Los Angeles/London: University of California Press).

Arentze, T.A., Ettema, D. and Timmermans, H.J.P. (2008) Incorporating time and money constraints in dynamic agent-based models of activity generation and time use: approach and illustration, *Transportation Research C*, 18, pp. 71-83.

Axhausen, K.W. and Gärling, T. (1992) Activity-based approaches to travel analysis: conceptual frameworks, models and research problems, *Transport Reviews*, 12, pp. 324-341.

Balmer, M., Meister, K., Rieser, K., Nagel, K. and Axhausen, K.W. (2008) Agent-based simulation of travel demand: Structural and computational performance of MATSim-T. Paper presented at the 2nd TRB Conference on Innovation in Travel Modeling, Portland, June 2008 http://www. matsim.org/node/179.

Batty, M. (1997) Cellular automata and urban form: a primer, *Journal of the American Planning Association*, 63, pp. 264-274.

Batty, M. (2005) *Cities and Complexity. Understanding Cities with Cellular Automata, Agent-Based Models and Fractals* (Cambridge, MA/London: MIT Press).

Batty, M. and Xie, Y. (1994) From cells to cities, *Environment and Planning B: Planning and Design*, 21, pp. 31-48.

Beckman, R.J., Baggerly, K.A. and McKay, M.D. (1995) *Creating Synthetic Baseline Populations*. LA-UR-95-1985 (Los Alamos, MN: Los Alamos National Laboratory).

Beckmann, K.J., Brüggemann, U., Gräfe, J., Huber, F., Meiners, H., Mieth, P., Moeckel, R., Mühlhans, H., Schaub, H., Schrader, R., Schürmann, C., Schwarze, B., Spiekermann, K., Strauch, D., Spahn, M., Wagner, P. and Wegener, M. (2007) *ILUMASS: Integrated Land-Use Modelling and Transport System Simulation* (Berlin: Deutsches Zentrum für Luft- und Raumfahrt) http://www.spiekermann-wegener.de/pro/pdf/ILUMASS_Endbericht.pdf.

Ben-Akiva, M.E., Bowman, J.L. and Gopinath, D. (1996) Travel demand model system for the information era, *Transportation*, 23, pp. 241-166.

Castiglione, J., Freedman, J. and Bradley, M. (2003) Systematic investigation of variability due to random simulation error in an activity-based microsimulation forecasting model, *Transportation Research*, 1831, pp. 76-88.

Chapin, F.S. and Weiss S.F. (1968) A probabilistic model for residential growth. *Transportation Research*, **2**, 375-390.

Clarke, M. and Holm, E. (1987) Microsimulation methods in spatial analysis and planning, *Geografiska Annaler*, 69B, pp. 145-164.

Clarke, M., Keys, P. and Williams, H.C.W.L. (1980) *Micro-Analysis and Simulation of Socio-Economic Systems: Progress and Prospects* (Leeds: School of Geography, University of Leeds).

de la Barra, T. (1989) *Integrated Land Use and Transport Modelling* (Cambridge, UK: Cambridge University Press).

de Nijs, T.C.M. (2009) Future land-use in the Netherlands: Evaluation of the National Spatial Strategy. In: Geertman, S., Stillwell, J. (Eds.) *Planning Support Systems: Best Practice and New Methods*. pp. 52-67 (Hedielberg/Berlin/New York: Springer).

Dowling, R., Holland, J. and Huang, A. (2002) *California Department of Transportation: Guidelines for Applying Traffic Microsimulation Software* (Oakland, CA: Dowling Associates Inc. http://www.ptvamerica.com/fileadmin/files_ptvamerica.com/library/Caltrans/Microsimapps/2002.pdf.

Echenique, M.H., Flowerdew, A.D.J., Hunt, J.D., Mayo, T.R., Skidmore, I.J. and Simmonds, D.C. (1990) The MEPLAN models of Bilbao, Leeds and Dortmund, *Transport Reviews*, 10, pp. 309-322.

Einstein, A. (1934) On the method of theoretical physics. *Philosophy of Science*, 1, pp. 163-169.

Engelen, G., White, R. and De Nijs, T. (2003) Environment Explorer: Spatial Support System for the Integrated Assessment of Socio-Economic and Environmental Policies in the Netherlands. *Integrated Assessment*, 4, pp. 97-105.

Ettema, D., Arentze, T. and Timmermans, H.J.P. (2009) Money talks: developing activity generation models based on time and money allocation. Paper presented at the International Choice Modelling Conference, Harrogate, UK.

Ettema, D., de Jong, K., Timmermans, H.J.P. and Bakema, A. (2007) PUMA: Multiagent modelling of urban systems. In: Koomen, E., Stillwell, J., Bakema, A. and Scholten, H.J. (Eds.) *Modelling Land-Use Change: Progress and Applications*. The Geojournal Library 90, pp. 237-258 (Amsterdam: Springer Netherlands)

Federal Highway Administration (2004) *Traffic Analysis Toolbox. Vol. III: Guidelines for Applying Traffic Microsimulation Software. Appendix E: Hypothesis Testing of Alternatives* (Washington, DC: US. Department of Transportation) http://ops.fhwa.dot.gov/trafficanalysistools/tat_vol3/.

Ferrand, N. (2000) Multi-reactive agents paradigm for spatial modelling. In: Fotheringham, A.S., Wegener, M. (Eds.) *Spatial Models and GIS: New Potential and New Models*, pp. 176-184 (London: Taylor & Francis).

Feldman, O., Simmonds, D. and Richmond, E. (2007a) *Household Location Modelling: Final Report. Part 1: Model Design*. Report for the Department for Transport (Cambridge: David Simmonds Consultancy) http://www.dft.gov.uk/pgr/ economics/rdg/hlm/modeldesign.pdf.

Feldman, O., Simmonds, D., Zachariadis, V., Mackett, R., Bosredon, M., Richmond, E and Nicoll, J. (2007b) SimDELTA – a microsimulation approach to household location modelling. Paper presented at the 11th World Conference on Transport Research, University of California at Berkeley http://www.davidsimmonds.com/index.php?action=download_resource&id=35&module=resource smodule&src=%40random47835850b71f0.

Fiorello, D., Huismans, G., López, E., Marques, C., Steenberghen, T., Wegener, M. and Zografos, G. (2006) *Transport Strategies under the Scarcity of Energy Supply*. Final Report of the EU project "STEPs – Scenarios for the Transport and Energy Supply and their Potential Effects", edited by A. Monzon and A. Nuijten. (Den Haag: Buck Consultants) *http://www.steps-eu.com/ reports.htm*.

Geraldes, P., Echenique, M.H. and Williams, I.N. (1978) A spatial economic model for Bilbao, *Proceedings of the PTRC Summer Annual Meeting*, pp. 75-94 (London: PTRC).

Goldner, W. (1971) The Lowry model heritage. *Journal of the American Institute of Planners*, 37, pp. 100-110.

Hägerstrand T. (1968) *Innovation Diffusion as Spatial Process* (Chicago: University of Chicago Press).

Hayashi, Y. and Tomita, Y. (1989) A micro-analytic residential mobility model for assessing the effects of transport improvement. In: *Transport Policy, Management and Technology – Towards 2001*, Selected Proceedings of the Fifth World Conference on Transport Research, pp. 91-105 (Yokohama/Ventura, CA: Western Periodicals).

Hunt, J.D., Abraham, J.E., De Silva, D., Zhong, M., Bridges, J. and Mysko, J. (2008) Developing and applying a parcel-level simulation of developer actions in Baltimore. Proceedings of the 87th

Annual Meeting of the Transportation Research Board, Washington, DC, January 2008 http://v8nu74s71s31g374r7ssn017uloss3c1vr3s.unbf.ca/~ming/document/Baltimore.pdf.

Kain, J.F. and Apgar, W.C. Jr. (1985) *Housing and Neighborhood Dynamics: A Simulation Study.* (Cambridge, MA: Harvard University Press).

Kreibich, V. (1979) Modelling car availability, modal split, and trip distribution by Monte Carlo simulation: a short way to integrated models, *Transportation*, 8, pp. 153-166.

Landis, J.D. (1994) The California Urban Futures Model: a new generation of metropolitan simulation models, *Environment and Planning B: Planning and Design*, 21, pp. 399-422.

Landis, J.D. and Zhang, M. (1998a) The second generation of the California urban futures model. Part 1: Model logic and theory, *Environment and Planning B: Planning and Design*, 25, pp. 657-666.

Landis, J.D. and Zhang, M. (1998b) The second generation of the California urban futures model. Part 2: Specification and calibration results of the land-use change submodel, *Environment and Planning B: Planning and Design*, 25, pp. 795-824.

Lautso, K., Spiekermann, K., Wegener, M., Sheppard, I., Steadman, P., Martino, A., Domingo, R. and Gayda, S. (2004) *PROPOLIS: Planning and Research of Policies for Land Use and Transport for Increasing Urban Sustainability*. PROPOLIS Final Report (Helsinki: LT Consultants) http://www1. wspgroup.fi/lt/propolis.

Lee, D.B. (1973) Requiem for large-scale models, *Journal of the American Institute of Planners* 39, pp. 163-178.

Lenntorp, B. (1976) *Paths in Time-Space Environment: A Time Geographic Study of Possibilities of Individuals*. Lund Studies in Geography 44 (Lund: Department of Geography, Royal University of Lund).

Lowry, I.S. (1964) *A Model of Metropolis*. RM-4035-RC (Santa Monica, CA: Rand Corporation).

Mackett, R.L. (1983) *The Leeds Integrated Land-Use Transport Model (LILT)*. Supplementary Report SR 805 (Crowthorne, Berkshire: Transport and Road Research Laboratory).

Mackett, R.L. (1985) Micro-analytical simulation of locational and travel behaviour. In: *Proceedings of the PTRC Summer Annual Meeting,* pp. 175-188 (London: PTRC).

Mackett, R.L. (1990) Comparative analysis of modelling land-use transport interaction at the micro and macro levels, *Environment and Planning A*, 22, pp. 459-75.

Marshall, S., Banister, D. (Eds.) (2007) *Land Use and Transport: European Research towards Integrated Policies* (Amsterdam/London: Elsevier).

Miller, E.J. and Salvini, P.A. (2001) The Integrated Land Use, Transportation, Environment (ILUTE) Microsimulation Modelling system: Description and current status. In: Hensher, D.A. (Eds.) *The Leading Edge in Travel Behaviour Research*. Selected Papers from the 9th International Association for Travel Behaviour Research Conference, Gold Coast, Queensland, Australia.

Moeckel, R. (2007) *Business Location Decisions and Urban Sprawl: A Microsimulation of Business Relocation and Firmography*. Dortmunder Beiträge zur Raumplanung 126 (Dortmund: Institute of Spatial Planning, University of Dortmund).

Nagel, K., Beckman, R.J. and Barrett, C.L. (1999) *TRANSIMS for Transportation Planning*. LA-UR 98-4389 (Los Alamos, NM: Los Alamos National Laboratory).

Nguyen-Luong, D. (2008) An integrated land-use transport model for the Paris Region (SIMAURIF): Ten lessons learned after four years of development. (Paris: IAURIF) http://mit.edu/11.521/proj08/readings/D_Mes_documentsDNLpredit3ERSA_2008article_SIMAURIF_10_lessons.pdf.

Orcutt, G., Greenberger, M., Rivlin, A. and Korbel, J. (1961) *Microanalysis of Socioeconomic Systems: A Simulation Study* (New York: Harper and Row).

Poeck, M. and Zumkeller, D. (1976) *Die Anwendung einer maßnahmenempfindlichen Prognosemethode am Beispiel des Großraums Nürnberg*. Proceedings of the DVWG Workshop "Policy Sensitive Models", Gießen.

Putman, S.H. (1983) *Integrated Urban Models: Policy Analysis of Transportation and Land Use* (London: Pion).

Putman, S.H. (1991) *Integrated Urban Models 2. New Research and Applications of Optimization and Dynamics* (London: Pion).

Salomon, I., Waddell, P., Wegener, M. (2002) Sustainable life styles? microsimulation of household formation, housing choice and travel behaviour. In: Black, W.R., Nijkamp, P. (Eds.) *Social Change and Sustainable Transport*. (Bloomington, IN: Indiana University Press), pp. 125-131.

Schelling, T.C. (1978) *Micromotives and Macrobehaviour* (New York/London: W.W. Norton & Company).

Ševcíková, H., Raftery, A. and Waddell, P. (2007) Assessing uncertainty in urban simulations using Bayesian melding, *Transportation Research* B, 41(6), pp. 652-659. http://www.urbansim.org/pub/Research/ResearchPapers/BMinUrbansim_TRB.pdf.

Simmonds, D (1999) The design of the DELTA land-use modelling package, *Environment and Planning B: Planning and Design*, 26, pp. 665-684.

Solow, R.M. (1973) Rejoinder to 'A comment on some uses of mathematical models in urban economics', *Urban Studies*, 10, p. 267.

Spiekermann, K. (2003) *The PROPOLIS Raster Module*. Deliverable D4 of PROPOLIS (Dortmund: Spiekermann & Wegener Urban and Regional Research) http://www.spiekermann-wegener.de/pro/pdf/PROPOLIS_D4.pdf.

Spiekermann, K. and Wegener, M. (2008) Environmental feedback in urban models, *International Journal of Sustainable Transport*, 2, pp. 41-57.

TRANSIMS (2009) http://tmip.fhwa.dot.gov/community/user_groups/transims.

Veldhuisen, J., Timmermans, J. and Kapoen, L. (2000) Microsimulation model of activity-travel patterns and traffic flows: specification, validation tests, and Monte Carlo error, *Transportation Research Record: Journal of the Transportation Research Board*, 1706, pp. 126-135.

Waddell, P. (1998a) An urban simulation model for integrated policy analysis and planning: residential location and housing market components of UrbanSim. Paper presented at the 8th World Conference on Transport Research, Antwerp.

Waddell, P. (1998b) UrbanSim Overview: http://urbansim.org.

Waddell, P. (2002) UrbanSim: Modeling urban development for land use, transportation and environmental planning, *Journal of the American Planning Association*, 68, pp. 297-314.

Wagner, P. and Wegener, M. (2007) Urban land use, transport and environment models: experiences with an integrated microscopic approach *disP* 170, pp. 45-56. http://www.nsl.ethz.ch/index.php/en/content/download/1550/9200/file.

Wegener, M. (1982) A multilevel economic-demographic model for the Dortmund region, *Sistemi Urbani*, 3, pp. 371-401.

Wegener, M. (1985) The Dortmund housing market model: A Monte Carlo simulation of a regional housing market. In: Stahl, K. (Ed.) *Microeconomic Models of Housing Markets.* Lecture Notes in Economic and Mathematical Systems 239, pp. 144-191 (Berlin/Heidelberg/New York: Springer).

Wegener, M. (1994) Operational urban models: state of the art. *Journal of the American Planning Association*, Vol. 60 (1), pp. 17-29. Reprinted in Reggiani, A., Button, K., Nijkamp, P. (Eds.) *Planning Models*. Classics in Planning 2, pp. 72-84 (Cheltenham, UK: Edward Elgar, 2006).

Wegener, M. (2001) *The IRPUD Model*. (Dortmund: Institute of Spatial Planning, University of Dortmund) http://www.spiekermann-wegener.de/mod/pdf/IRPUD_Model_2001.pdf.

Wegener, M. (2004) Overview of land-use transport models. In: Hensher, D.A., Button, K.J. (Eds.) *Transport Geography and Spatial Systems*. Handbook 5 of Handbook in Transport, pp. 127-146 (Kidlington, UK: Pergamon/Elsevier Science).

Wegener, M. (2008) *SASI Model Description*. Working Paper 08/01 (Dortmund: Spiekermann & Wegener Urban and Regional Research) http://www.spiekermann-wegener.de/mod/pdf/AP_0801.pdf.

Wegener, M. and Bökemann, D. (1998) *The SASI Model: Model Structure*. Berichte aus dem Institut für Raumplanung 40 (Dortmund: Institute of Spatial Planning, University of Dortmund) http://www.raumplanung.uni-dortmund.de/irpud/fileadmin/irpud/content/documents/publications/ber40.pdf.

Wegener, M. and Spiekermann, K. (1996) The potential of microsimulation for urban models. In: Clarke, G. (Ed.) *Microsimulation for Urban and Regional Policy Analysis*. European Research in Regional Science 6, pp. 146-163 (London: Pion).

White, R. and Engelen, G. (1994) Cellular dynamics and GIS: modelling spatial complexity, *Geographical Systems*, 1, pp. 237-253.