Multimethod Modeling and Simulation Supporting Urban Planning Decisions

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Abstract This chapter reflects on why multimethod simulation is gaining increasing numbers of supporters. The chapter illustrates advantages and disadvantages of combining different modeling methods and presents a specialized software tool—the MASGISmo simulation platform. The theoretical discussion is supported with results obtained from different simulation projects. The chapter argues how an urban development model using a multimethod approach can support policy makers and urban planners in implementing robust and better acknowledged planning measures. Agent-based modeling (ABM) is used to enable model users to interpret and react to information from different levels of the urban spatial hierarchy within the simulation. The contribution also points out the value added by combining ABM with system dynamics modeling along with the use of geographical information system data. Finally, the chapter discusses how a new way of real stakeholder interactivity within the simulation can be achieved in order to improve the model.

Keywords Multimethod-modeling · Simulation platform · Agent-based modeling · Multi-agent system modeling · System dynamics modeling · Geographic information systems · Urban planning · Spatial simulation · Decision support system

Evolving regions or cities are often based on an interaction between top-down planning decisions and bottom-up processes. This interaction allows stable structures to develop, with a complex organization and a connectivity-rich network (Salat and Bourdic 2012, p. 60). Owing to the high complexity present on and between various spatial and hierarchical levels, computer models have proven useful in the analysis of different urban developmental paths. Complexity in this

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C. Walloth et al. (eds.), *Understanding Complex Urban Systems: Multidisciplinary Approaches to Modeling*, Understanding Complex Systems,
DOI: 10.1007/978-3-319-02996-2_2,

context means a (non-linear) feedback structure connecting the elements within one and on different levels of the system.

Urban modeling was defined by Batty as follows:

> The process of identifying appropriate theory, translating this into a mathematical or formal model, developing relevant computer programs and then confronting the model with data so that it might be calibrated, validated and verified prior to its use in prediction. (Batty 1976, p. 3)

Two commonly used modeling methods, system dynamics (SD) and agent-based modeling (ABM), will be introduced in the following paragraphs. Subsequently, usage of data from geographical information systems (GIS) shall be presented, showing how it can be used to enhance the model. Finally, the potential integration of local stakeholders to improve the model is shown.

1 Urban and Regional Modeling Methods

1.1 SD Modeling

The fundamentals of SD modeling were determined by Jay Wright Forrester in the mid-1950s. SD modeling is a method that allows the understanding of the behavior of complex systems over time.

The System Dynamics Society offers the following definition:

> System dynamics is a computer-aided approach to policy analysis and design. It applies to dynamic problems arising in complex social, managerial, economic, or ecological systems—literally any dynamic systems characterized by interdependence, mutual interaction, information feedback, and circular causality. (System Dynamics 2012)

Feedback serves as the differentiating descriptor in this context. Feedback refers to the situation of X affecting Y and Y in turn affecting X, possibly through a chain of causes and effects. Furthermore, complex systems are driven by more than one simple feedback loop—they commonly include positive-feedback loops involving exponential growth processes interacting with negative, goal-seeking loops.

So, in general, it can be stated that SD modeling describes complex systems through the use of feedback loops, stocks and flows. Stocks characterize the state of the system. They are the ‘memory’ of a system and enable us to describe the current status of a system. Flows affect the stocks via inflow or outflow and interlink the stocks within a system. The resulting structure of the system, built up with stocks and flows, determines the behavior of the system. The following Fig. 1 depicts a simple Stock-Flow example. In principle, each SD model is built up with these building blocks. Notice feedback structures are included, e.g. between Inflow of Stock A and Stock A itself.

Together with John Collins, Forrester worked on SD modeling of urban systems and published *Urban Dynamics* in 1969 (Forrester 1969). One of the main reasons

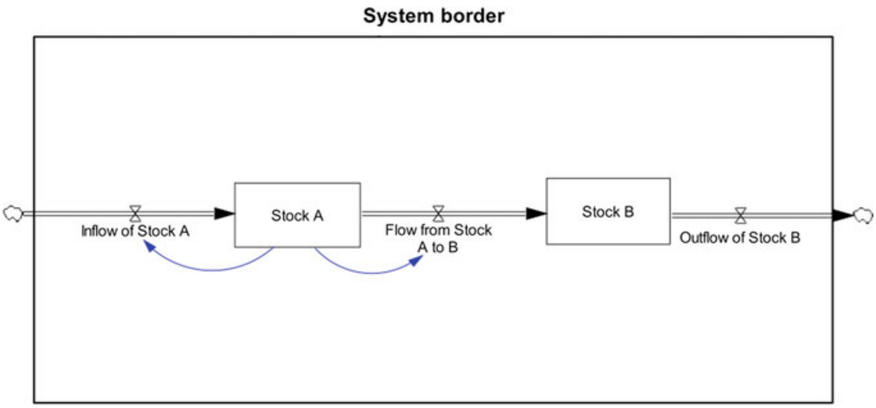

Fig. 1 Simple stock-flow example. © AIT

their collaboration focused on urban systems was Forrester's discovery that cities behave counter-intuitively. For example, corrective action suggested by urban planners is often ineffective or worsens a problem, because a simple cause and effect connection is ignored. Forrester was surprised by the success the book enjoyed and noted that "Urban Dynamics was the first of [his] modeling works that produced strong, emotional reactions" (Forrester 1995, p. 8).

The process of model building was, from the very beginning, supported by specialized software, which was one main reason why this method has become widespread over the last few decades. Today, a variety of tools exist, such as Stella/iThink (Stella 2012), Powersim (Powersim 2012) and Vensim (Vensim 2012).

Despite the benefit of understanding the behavior of complex feedback systems with simple 'building blocks' like stocks and flows that the SD method provides, there are major disadvantages. For example, emergent spatial development—i.e. the self-organized development of new and coherent structures, patterns, and properties (Goldstein 1999, p. 49)—cannot be modeled, since new stocks and flows cannot be generated during a simulation. However, emerging patterns are an important factor of sustainable regional development (cf. Salat and Bourdic 2012, p. 11). Therefore, a combined method that offers the advantage of SD modeling as well as the ability to analyze spatial development and emerging properties can help to improve regional (urban) modeling. Such a method is ABM.

1.2 *Agent-Based Modeling*

ABM, also sometimes called individual-based modeling (IBM) or multi-agent systems modeling (MAS), has gained increasing importance in the studies of social and economic systems. It has often been used to improve the understanding of a wide range of problems and to help forecast the effects of top-down decisions on the micro-level. Applications include the emergence of cooperation (Holland and Miller 1991) and the influence of expectations, e.g. on the stock market (Axelrod 1997a, b).

A famous early example of ABM used in urban modeling concerned the emergence of racial segregation in cities (Schelling and Hamburger 1979). However, only over the last five to ten years has ABM been receiving increased attention from the spatial development modeling community (land-use modeling as well as urban planning). It has been recognized that ABM offers a way of incorporating the influence of human decision making on land-use in a formal and spatially explicit way, taking into account social interaction, adaptation, and decision-making on different spatial and (or) hierarchical levels (Matthews et al. 2007, p. 1448).

In contrast to SD models, which are composed of stocks and flows, the building blocks of ABM and in particular the concept of agents itself are not clearly defined. However, it is argued by Jennings et al. (1998, p. 8) that ABM uses three key terms: 'situatedness', 'autonomy', and 'flexibility'. Here, 'situatedness' means that an agent receives information about the environment from sensors and, subsequently, can perform actions, which, in turn, can influence the environment. 'Autonomy' means that an agent can act solely based upon its objectives and the system's internal state, without any direct external influence. 'Flexibility' means that the agent has the ability to change its behavior, for instance when it needs to adapt or learn from others. Hence, in summary we can say that agents are situated in and interacting with their environment and are capable of changing their behavior to reach their individual objectives.

ABM has several disadvantages compared to SD modeling, e.g. a higher need of data to calibrate. Moreover, ABM produces results that are more difficult to evaluate. This causes a much higher effort for model validation and verification (model evaluation) as for instance Fagiolo et al. (2006) and Werker and Brenner (2004) discussed. Although it does not always make sense to use ABM, it is especially the ability to analyze spatial development and social behavior that makes ABM very valuable in the context of regional (urban) development models (cf. Fig. 2). ABM enables us to investigate and understand patterns emerging out of self-organization among individual agents, which leads to, e.g. segregation within regions or cities.

Figure 2 depicts two different types of agents and their behavior according to their preference for living close to their own type. The model is based on the work of Schelling and Hamburger (1979) about social systems.

2 Finding the Best Modeling Method

In general, Lorenz and Jost argue that modelers often overlook other modeling methods, simply because they cannot "differentiate and apply alternative methods" which differ from the ones they are familiar with. Often, it is noticeable that

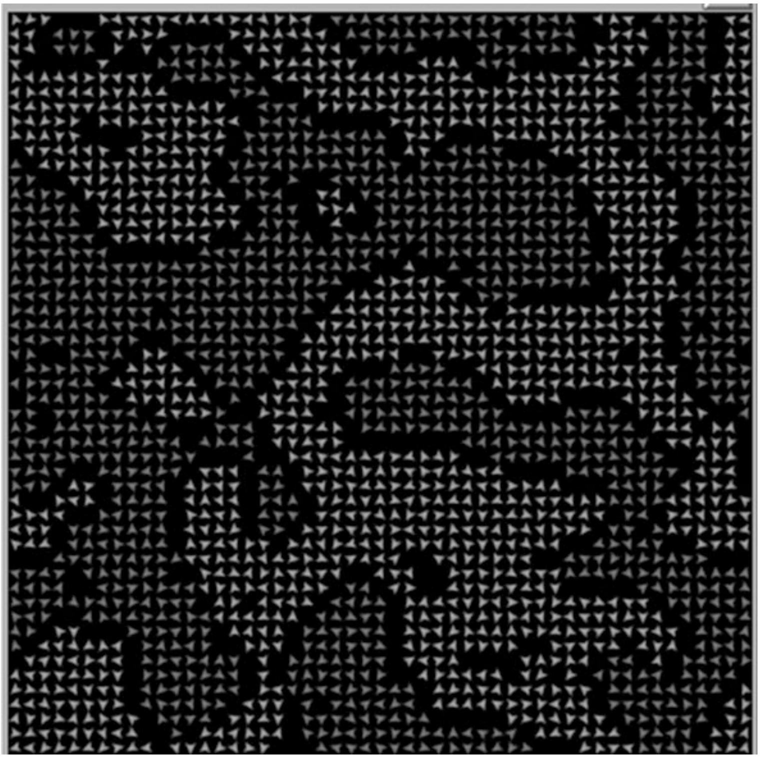

Fig. 2 Agent-based models are spatially explicit and allow us to visualize emerging patterns in cities and regions. Screenshot of the segregation model made with Netlogo © Wilensky (1997 and 1999)

modelers adopt a too strict methodological stance even where the combined use of different methods would be more appropriate (Lorenz and Jost 2006, p. 2).

Furthermore, they argue that different modeling methods would be easier to apply if software tools were readily available which offer the combined use of different modeling methods for so-called multimethod modeling. For example, the dissemination of SD modeling and ABM was significantly supported by the availability of specifically designed software tools, some of which greatly enhanced the usability of both methods (e.g., Vensim/Stella for stock flow and causal loop diagrams for SD modeling and Repast/Netlogo/Anylogic (Repast 2012; Netlogo 2012; Anylogic 2012) for ABM). In the last five to ten years, several different multimethod modeling software tools have been released and it can be assumed that this has not come to an end.

Lorenz and Jost argue that finding the most appropriate modeling method rests on the clarification of the object to be modeled, the modeling method to be applied, and the modeling purpose (Lorenz and Jost 2006). In this context, the object to be modeled stands for the system under investigation, the “what to simulate”. The modeling method stands for a standardized combination of techniques and tools (Lorenz and Jost 2006, p. 3). For example, the SD modeling method stands for the technique of working with causal loop and stock flow diagrams and the use of specialized software tools (e.g. Vensim/Stella). On the other hand, the ABM method stands for the technique of defining agents through individual rules of behavior and the use of specialized software tools (e.g. Repast/Netlogo). The representation of the object to be modeled through the data available as, e.g., an object in a world of static structures or in a world of dynamic changes, as well as the detail of the data largely influence the selection of the modeling method. The purpose is the motivation behind any modeling attempt and, hence, a major factor in selecting the modeling method. For example, the purpose of modeling for policy-makers might be to solve a problem by establishing top-down measures, influencing social behavior and emergent phenomena. Such a purpose calls, on the one hand, for a modeling of the macro-level on which top-down measures can be exerted and, on the other hand, for a modeling of the micro-level on which individual actions might give rise to emergent phenomena visible on the macro-level.

Whenever two or more such levels can be distinguished in the object to be modeled, multimethod modeling might yield better results than one modeling method alone. However, it is to be considered that applying a familiar modeling method might still be better than adopting the latest one without fully understanding it. Also, it is to be considered that multimethod modeling does not only have advantages, as model evaluation often becomes more difficult with the number of approaches combined (Barlas 1989; Windrum et al. 2007; Fagiolo et al. 2006).

3 MASGISmo: A Multimethod Modeling Tool

In the beginning of ABM, spatial modeling of an agent did not include geographic information. The same was the case in the beginning of combined SD modeling and ABM (Gebetsroither 2009). Geographic information is, however, important in the simulation of, e.g., regional development, especially if local stakeholders are involved in the discussion of the result: Geographic information may enable local stakeholders to intensify their engagement in the discussion of simulation results. Therefore, especially when local stakeholders (e.g., within a participatory urban planning process using modeling) are involved, the inclusion of data from geographic information systems (GIS) represents a major advancement. Nowadays, people are used to easily accessible geographic data, thanks to ubiquitous services such as Google Maps or Open Street Maps.

Today, multimethod modeling including GIS data is possible through specifically designed software tools like Anylogic Netlogo, Repast Symphony, and MASGISmo (Multimethod Agent-based, System Dynamics and GIS modeling platform (MASGISmo 2012)). MASGISmo makes use of GIS data for complex spatial analyses, while the other software tools use their GIS functionality mainly for obtaining information about the agent's location. MASGISmo in turn enables users to analyze the environment of an agent in manifold ways within the platform, e.g., the location can be used to estimate its influence on the agent's behavior. It was developed at the Austrian Institute of Technology (AIT), the author's affiliate institution, especially to enable multimethod modeling.

MASGISmo combines SD modeling, ABM, and GIS data analyses. Combining SD and ABM is based on the pioneering works of Akkermans and Scholl (Akkermans 2001; Scholl 2001a, b) and Pourdehnad, Schieritz and Milling (Pourdehnad 2002; Schieritz and Milling 2003; Schieritz and Groessler 2003). MASGISmo combines SD modeling through inclusion of Vensim and ABM through inclusion of Repast. Enhancing the spatial capabilities of the ABM module has enabled the inclusion of GIS data analyses within the multimethod platform. This allows users of MASGISmo to develop multimethod models simulating spatially explicit actions of agents changing land-use and to spatially analyze the results of these actions. The calculation of new geographic maps out of the existing ones can be performed by using simple arithmetic operations and the agents' spatial movements by transforming land-use of single cells into steady land-use transitions. This process is part of the spatial data analysis features of MASGISmo and is one main difference to other tools like Anylogic.

The development of the simulation platform MASGISmo is predominantly determined by the requirements of the projects it serves, i.e. the objects to be modeled and the modeling purposes. Almost with every model built up with MASGISmo, new functionalities for the platform are developed, serving other future modeling purposes.

The screenshot below presents the graphical user interface (GUI) of one MASGISmo simulation showing some results (Fig. 3). Three main parts characterize MASGISmo's GUI: first the general simulation controls, second the interactive toolset and third the illustration tools such as dynamic results map, GIS layer legend and the overview map. This depicted GUI is, on the one hand, an example of the current stage of MASGISmo's development while, on the other hand, it was explicitly built for the specific purpose of the simulation of different urban development scenarios. In this use case, importing GIS data of, e.g., different urban zoning plans, new infrastructure, or shopping centers and companies enables decision makers to simulate different spatially explicit development scenarios.

Besides, since multimethod modeling should enable the user to interact with and retrieve results from the models of the different integrated methods, a new interface was developed to steer the SD models (built with Vensim, running in the background) and analyze their results within the MASGISmo GUI. Further details on building models using MASGISmo are detailed elsewhere (Gebetsroither 2009, p. 63 and MASGISmo 2012).

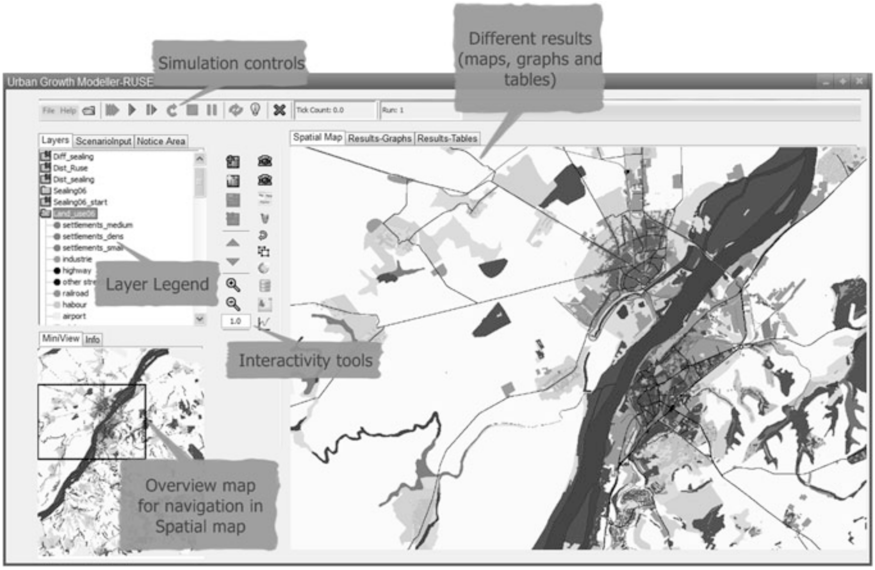

Fig. 3 Screenshot of MASGISmo's current GUI enhanced within the urbanAPI project, © AIT

4 Examples of Multimethod Modeling

In order to exemplify the use of multimethod modeling, in the following I will present the application of MASGISmo in the Dead Sea project and in the urbanAPI project. For the first project, the modeling purpose was to increase the sustainability of water management in the Dead Sea Basin. For the urbanAPI project, the modeling purpose is to support urban (regional) planning decisions with simulations and to improve regional policy making in European initiatives (European Commission 2012).

4.1 The Dead Sea Project

In the Dead Sea project two levels of objects to be modeled justified multimethod modeling. First, the region's current political framework, shaped by territorial and water claims, determined a top-down system behavior to be modeled by SD. Second, the local (spatially explicit) citizens' reactions determined a bottom-up system behavior to be modeled by ABM. The self-organization from bottom-up—expected as a reaction to the top-down political framework—would not have been possible if only SD modeling had been used.

The multimethod model was used to simulate spatially explicit future land-use scenarios, which were first introduced into the model of the region as probabilities of land-use change, based on current land-use and historical trends (Gebetsroither and Loibl 2007a). These probabilities of land-use change and the expected effects of political top-down interventions (e.g., on water prices and availability) are changing the spatial attractiveness of different areas within the entire modeled region. The changes in spatial attractiveness were then introduced into the ABM. Results of the ABM simulation included spatially explicit visualizations of future land-use scenarios, which helped to evaluate the effectiveness of political top-down interventions on local development based on defined criteria of, e.g., land availability for settlements, industrial, touristic, and agricultural activity, and natural environment (Gebetsroither and Loibl 2007b). Figure 4 depicts a scenario of land-use changes produced by the interactions between political top-down interventions and agents' activities between 2005 and 2025. The regions with significant land-use changes can be easily noticed (marked with green circles and black ellipsoids in the figure).

In the Dead Sea project, SD modeling produced the input for ABM, which in turn produced scenarios of land-use change over time, considering political top-down interventions. The SD model was used to model the physical water network with its pipelines and water storages. Also, the water demand, depending on water prices, has been simulated within the SD model. The spatially explicit results of potential land-use changes let decision makers draw conclusions on agents' reactions to interventions, test scenarios, choose those which produced more sustainable results, and to discuss regional and urban planning or economic development approaches with both public and private stakeholders. Even for the modelers and the local scientific experts, it was remarkable that, due to the use of geographic maps for the visualization of the results, new insights into the system's behavior were gained. For example, it could be depicted how a planned resettlement of about one million emigrated Palestinians would change the current land-use in the region (see the black ellipsoids in Fig. 4).

4.2 UrbanAPI Project

Another application of multimethod modeling will be developed within the urbanAPI project (urbanAPI 2012). Thereby, an urban growth model, similar to the Dead Sea project, will be established. The modeling purpose is to support policy makers' decisions on different urban development paths. Here as well, top-down policies and demographic macro-developments meet bottom-up processes and justify the use of multimethod modeling.

The urbanAPI project uses SD modeling, first, to simulate regional economic effects of top-down decisions and, second, to simulate different demographic developments. The ABM module of MASGISmo is used to simulate in a spatially explicit way the migration of households and entrepreneurs in the region around the cities Ruse (Bulgaria) and Giurgiu (Romania). This requires data on individual (agents') preferences and self-organization processes such as, e.g., social

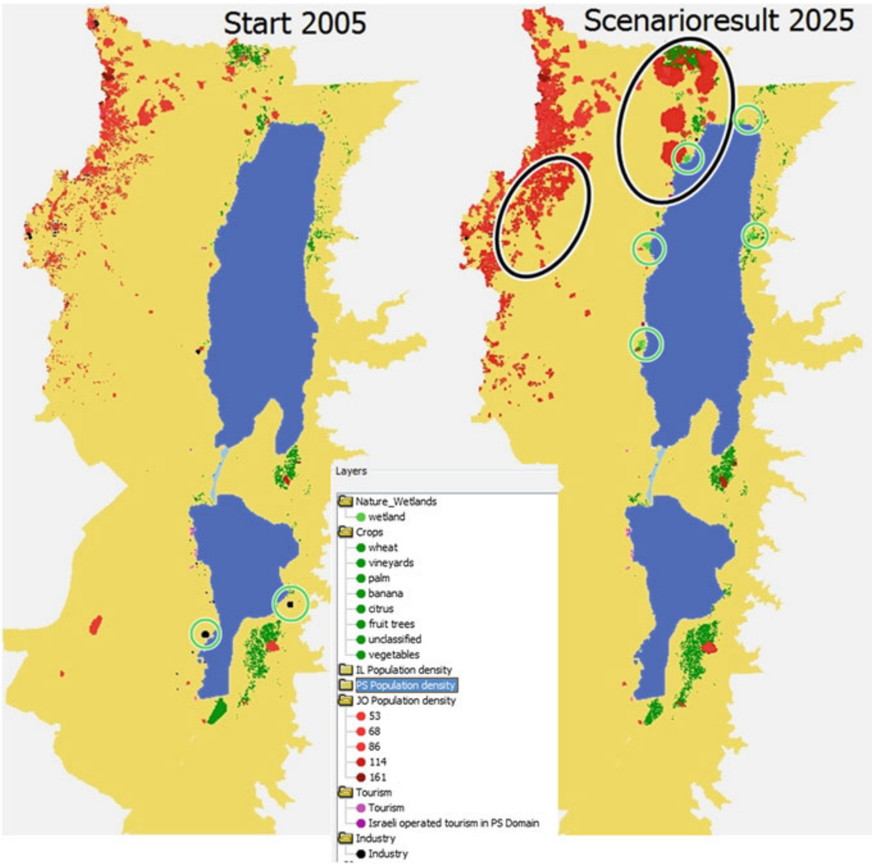

Fig. 4 Spatial development maps depicting the original land-use 2005 (*left*) and a scenario result for 2025 (*right*). Hot-spot areas are marked with *green circles* and *black ellipsoids*. A part of the legend of different land-uses is shown in-between the maps. © AIT

segregation, to be introduced into the ABM. This data—the quality of which largely determines the model's overall quality—is being drawn from the analysis of the region's historical spatial development. In the course of these historical spatial analyses, maps are produced, showing, e.g., the distances between points of interest or the household density at a certain point in time (cf. Fig. 5). From these maps, probabilities can be deduced for different agents migrating between different areas in the future and, hence, for probability maps of different types of land-use (cf. Corine Land Cover (Corine 2012)).

The four different maps in Fig. 5 show exemplarily three distance maps (in the two maps on the left the distance increases from red to green and further to blue, and in the map on the right the distance increases from green to red) and a map depicting household density (the density increasing from green to red). The model

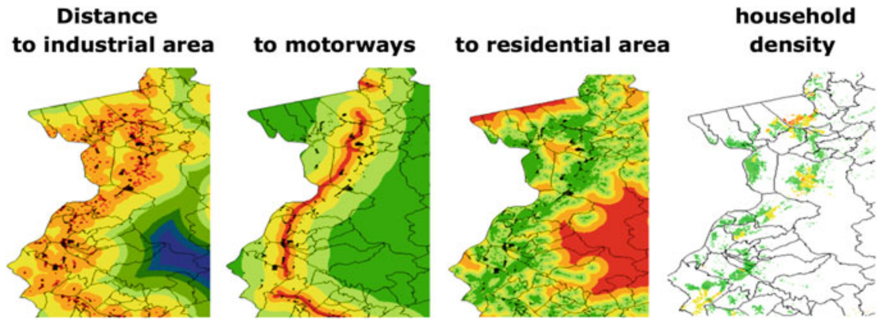

Fig. 5 Example of spatial analysis maps. © AIT

assumes that this information is used by the individual agents, according to their preferences, to decide where to move. The agents' preferences are extracted from historical data analyses revealing, e.g., where people have moved in the past in correlation to distances and densities as shown in the maps (Fig. 5). For example, data analysis showed that people moved to areas with lower household density. Further, multivariate correlation analysis showed the attractiveness of new industrial sites, influencing people's decisions where to move and, hence, impacting land-use. This kind of preference analysis is a basis for modeling different regional and urban development paths considering the individual agent's actions.

Figure 6 shows very early results of two regional development paths based on historical trends of the population development in the region and on different assumptions on the agents' preferences (in the left picture, the agents prefer to move to rural areas, whereas on the right picture the agents prefer to live in the city).

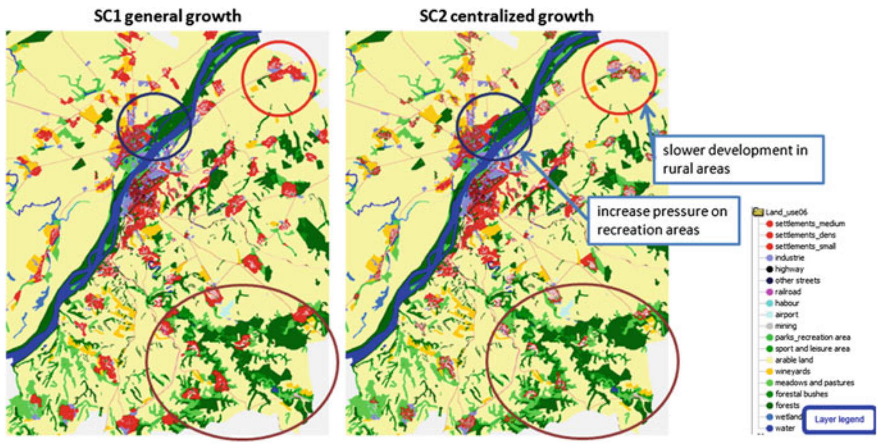

Fig. 6 urbanAPI simulation results showing two alternative urban development paths (after 20 years) for evenly distributed (*left*) and centralized (*right*) growth. The main differences between both scenarios are encircled. © AIT

5 Challenges of Multimethod Modeling in an Urban and Regional Context

The urbanAPI project, in the course of its first year, has raised a number of challenges that are symptomatic to urban and regional modeling. As mentioned above, the quality of an ABM hinges on the quality of the available data of agents' behavior.

Despite the above-mentioned thorough (multivariate correlation) analyses of the historical spatial development, an agent's behavior can only be determined to a certain extent. On the one hand, an extensive amount of historical information is necessary in order to get appropriate results. On the other hand, historical development is influenced by social conditions and political frameworks, which change over time. For example, a major change in the political framework occurred with the fall of the communist regimes and the start of the transition period in 1989/1990. Since then, people could have changed their living preferences, moving away from the industrial sites and closer to recreational areas. The analyses of the historical spatial development will show if this was really the case.

In order to reduce the impact of particular historical events in the simulation of future scenarios, a new approach is introduced. In the urbanAPI project, the author of this chapter plans to interact with local actors by using LimeSurvey, an open source survey application, over the Internet (LimeSurvey 2012). LimeSurvey will be directly connected to MASGISmo, thereby integrating the local actors' current preferences. Local actors are in this context real persons, stakeholders, whereas agents are used as artificial entities acting solely within the simulation model.

Thus, internet polls will help to refine the data on the perceived attractiveness of different areas of the region in relation to different potential urban planning scenarios which will be presented to the local actors. This means that each participant in the internet poll adds (and alters) data of the local probability layers for different land-uses and, hence, all the participants change the simulation in an iterative process. Eventually, with this method, the model should become 'better' in the sense that it reflects the local agents' actual behaviors. The behavior of the agent is dynamically changing (hence, current behavior can hardly be revealed by historical analysis), since agents can evaluate their own decisions and interact or adapt to the behavior of other agents (Benenson 2004, p. 3).

It is expected that such 'real-time' data can help urban planners and politicians to better understand the self-organization resulting from the local agents' individual decisions. The urbanAPI project will thus show the benefits of such an interactive 'real-time' approach in multimethod modeling—provided a sufficient number of local actors will take part in the surveys, which is another point to be verified by this experiment.

The interaction with local stakeholders via internet designed to improve the data on agents' behaviors is a relatively new concept that combines computer agents' and local actors' behaviors (Guyot and Honiden 2006, p. 2). It is assumed that it can increase the sustainability of urban development plans and make the citizens accept these plans more easily since it directly involves the citizens. In general, this approach aims to enable policy makers to integrate timely feedback on new infrastructure and planning guidelines into an alternative set of urban development paths. To introduce the method of (social) surveys is another step enhancing the multimethod modeling techniques beyond combining SD, ABM and GIS modeling.

6 Summary and Conclusion

Modelers such as Lorenz and Jost (2006), Akkermans (2001), Scholl (2001a, b), Pourdehnad et al. (2002), Schieritz and Milling (2003) and Schieritz and Goessler (2003) argue that we have to use combined modeling methods, because each method has its own individual research field in which it is most appropriately used. Furthermore, modeling real world phenomena needs to combine different research fields. Systems including the interaction between society and natural resources (land area can also be seen as a natural resource), determined by agents' actions that develop at different levels (micro and macro), are often better modeled using different methods.

Political decisions, for instance, take place on the macro-level, which, in turn, affects the micro-level. Often, decision makers on the macro-level (the users of the model) need to study the (self-organized) reactions of the agents on the micro-level on potential policy changes. In that way, the potential development at the micro-level influences the macro-level, the political decisions, in a feedback loop. This would not be possible if only a top-down method such as SD modeling was used.

History has shown that the development of proper simulation software was important for the development and circulation of SD and ABM (Gebetsroither 2009). Admittedly, such a development will be even more important in the case of multimethod modeling, because modelers tend to use software tools which are familiar to them, even if those tools may not be the most appropriate for their goals.

MASGISmo, a multimethod simulation platform developed over the past several years, can be used as such a tool that successfully integrates ABM, SD, as well as GIS data and analysis. The two examples provided have demonstrated how multimethod modeling can be useful in two typical cases of urban and regional development.

It is particularly in urban and regional modeling that the inclusion of individual agents' behaviors helps to better understand the system's overall behavior. The inclusion of real-time data on local agent behaviors (preferences) is now being conducted in the urbanAPI project. This makes the model come closer to the reaction of local actors and therefore it is expected to yield more realistic simulations.

Ultimately, by combining different methods, scientists with different backgrounds engage with several fundamental questions in their respective fields, such as how to build a section of an integrated model or how to parameterize and evaluate it. If these questions receive the right answers, then the strong points of each approach can be combined while their weaknesses can be mitigated.

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http://www.springer.com/978-3-319-02995-5

Understanding Complex Urban Systems: Multidisciplinary Approaches to Modeling
Walloth, C.; Gurr, J.M.; Schmidt, J.A. (Eds.)
2014, XI, 158 p. 36 illus., Hardcover
ISBN: 978-3-319-02995-5