On Cells and Agents – Geosimulation of Urban Sprawl in Western Germany by Integrating Spatial and Non-Spatial Dynamics

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„Unter sone große Stadt, mit all ihr Jebumms und Jemäuer,
da is ja ooch noch Erde drunter, Sand, Lehm und Wasser, nich?
Und in'n Menschen sein Kopp, da sind Jedanken inne, und Wörter,
und denn det Jeträumte, det wird immer mehr, det wächst alles,
et weiß nur noch keener, wo det mal hin soll."
(Carl Zuckmayer, *Der Hauptmann von Köpenick*)

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Glossary

AI	Artificial intelligence
AUC	Area under curve
ATKIS	Amtliches Topographisch-Kartographisches Informationssystem
BLR	Binomial logistic regression
BORISplus	Zentrales Informationssystem der Gutachterausschüsse und des Oberen Gutachterausschusses für Grundstückswerte über den Immobilienmarkt in Nordrhein-Westfalen
CA	Cellular automaton
CWD	Cost-weighted distance
DF	Density function
DNA	Desoxyribonukleinsäure
DPSIR	Drivers, pressures, states, impacts, and responses
EEA	European Environment Agency
GIS	Ggeographic information systems
GLP	Global Land Project
GMES	Global Monitoring for Environment and Security
LAG 21 NRW	Landesarbeitsgemeinschaft Agenda 21 NRW
LANDSAT-ETM+	LANDSAT-Enhanced Thematic Mapper Plus
LANDSAT-TM	LANDSAT-Thematic Mapper
LANDSAT-MSS	LANDSAT- Multispectral Scanner
IDW	Inverse distance-weighted
IPCC	Intergovernmental Panel on Climate Change
IT NRW	Landesbetrieb für Information und Technik NRW
MBWSV	Ministerium für Bauen, Wohnen, Stadtentwicklung und Verkehr des Landes Nordrhein-Westfalen
MC	Monte Carlo iterations
MRV	Multiple resolution validation
MUNLV	Ministerium für Klimaschutz, Umwelt, Landwirtschaft, Natur- und Verbraucherschutz des Landes Nordrhein-Westfalen
MWEIMH	Ministerium für Wirtschaft, Energie, Bauen, Wohnen und Verkehr des Landes Nordrhein-Westfalen
NIMBY	Not in my backyard
NRW	North-Rhine Westphalia
NRWPro	Projekt „Visualisierung von Landnutzung und Flächenverbrauch in NRW mittels Satelliten- und Luftbildern“
OOP	Object-oriented programming
RBF	Gaussian radial basis function kernel
ReHoSh	Residential Mobility and the Housing Market of Shrinking City Systems
ROC	Receiver operating characteristic

RuhrFIS	Flächeninformationssystem Ruhr
SLEUTH	Slope, Land use, Exclusion, Urban, Transport, Hillshade
SVM	Support vector machines
UEC	Urban entertainment centers
UGM	Urban Growth Model
UGMr	Urban Growth Model with reduced input data sets
UGMr-AR	Urban Growth Model with reduced input data sets and area restrictions as exclusion layer
UGMr-BLR	Urban Growth Model with reduced input data sets and a probability map derived by binomial logistic regression as exclusion layer
UGMr-SVM	Urban Growth Model with reduced input data sets and a probability map derived by support vector machines as exclusion layer
UNEP	United Nations Environment Programm
XULU	eXtendable Unified Land Use modeling platform

Abstract

Urban sprawl is one of the most challenging land-use and land-cover changes in Germany implicating numerous consequences for the anthropogenic and geobiophysical spheres. While the population and job growth rates of most urban areas stagnate or even decrease, the morphological growth of cities is ubiquitous. Against this backdrop, the quantitative and qualitative modeling of urban dynamics proves to be of central importance. Geosimulation models like cellular automata (CA) and multi-agent systems (MAS) treat cities as complex urban systems. While CA focus on their spatial dynamics, MAS are well-suited for capturing autonomous individual decision making. Yet both models are complementary in terms of their focus, status change, mobility, and representations. Hence, the coupling of CA and MAS is a useful way of integrating spatial pattern and non-spatial processes into one modeling infrastructure.

The thesis at hand aims at a holistic geosimulation of the future urban sprawl in the Ruhr. This region is particularly challenging as it is characterized by two seemingly antagonistic processes: urban growth and urban shrinkage. Accordingly, a hybrid modeling approach is to be developed as a means of integrating the simulation power of CA and MAS. A modified version of SLEUTH (short for Slope, Land-use, Exclusion, Urban, Transport, and Hillshade) will function as the CA component. SLEUTH makes use of historic urban land-use data sets and growth coefficients for the purpose of modeling physical urban expansion. In order to enhance the simulation performance of the CA and to incorporate important driving forces of urban sprawl, SLEUTH is for the first time combined with support vector machines (SVM). The supported CA will be coupled with ReHoSh (Residential Mobility and the Housing Market of Shrinking City Systems). This MAS models population patterns, housing prices, and housing demand in shrinking regions. All dynamics are based on multiple interactions between different household groups as well as stakeholders of the housing market.

Moreover, this thesis will elaborate on the most important driving factors, rates, and most probable locations of urban sprawl in the Ruhr as well as on the future migration tendencies of different household types and the price development in the housing market of a polycentric shrinking region. The results of SLEUTH and ReHoSh are loosely coupled for a spatial analysis in which the municipal differences that have emerged during the simulations are disaggregated. Subsequently, a concept is developed in order to integrate the CA and the MAS into one geosimulation approach. The thesis introduces semi-explicit urban weights as a possibility of assessing settlement-pattern dynamics and the regional housing market dynamics at the same time. The model combination of SLEUTH-SVM and ReHoSh is finally calibrated, validated, and implemented for simulating three different scenarios of individual housing preferences and their effects on the future urban pattern in the Ruhr. Applied to a digital petri dish, the generic urban growth elements of the Ruhr are being detected.

Kurzfassung

Die Zunahme von Siedlungs- und Verkehrsflächen und die damit verbundenen ökologischen Probleme wie Landschaftszerschneidung oder Flächenversiegelung stellen in Deutschland eine noch nicht gelöste Herausforderung dar. Selbst in schrumpfenden Regionen ist eine flächenhafte Ausweitung von Siedlungs- und Verkehrsflächen in das städtische Umland hinein, *urban sprawl*, zu beobachten. Die Landnutzungsmodellierung beider Großtrends kann Aufschlüsse über Prozesse, Ursachen und Folgen von *urban sprawl* im sozialen wie ökologischen Bereich geben. Modelle der Geosimulation wie Zelluläre Automaten (CA) und Multi-Agenten Systeme (MAS) fassen Städte als Systeme auf und versuchen in ihrem Modellansatz die Komplexität dieser zu erfassen. Während sich CA auf die räumliche Dynamik von Siedlungen fokussieren, simulieren MAS Verhaltensänderungen von städtischen Entscheidungsträgern. Hinsichtlich ihres Fokus, der Statusänderungen ihrer Entitäten, deren Mobilität und ihrer Repräsentation verhalten sich CA und MAS komplementär zueinander und werden dadurch als ideal angesehen, die Modellierung räumlicher Muster und nicht-räumlicher Prozesse von *urban sprawl* in einen einzigen Modellansatz zu integrieren.

Das Ziel der vorliegenden Arbeit ist die holistische Geosimulation des zukünftigen *urban sprawl* im Ruhrgebiet. Die Untersuchungsregion stellt hohe Herausforderung an urbane Landnutzungsmodelle, da sie die scheinbaren antagonistischen Dynamiken von morphologischem Wachstum und wirtschaftlicher wie demografischer Schrumpfung in sich vereint. Angesichts dessen wird in der vorliegenden Arbeit ein hybrider Modellansatz verfolgt, der die Simulationsfähigkeiten von CA und MAS kombiniert. Eine modifizierte Version von SLEUTH (Slope, Land-use, Exclusion, Urban, Transport, and Hillshade) fungiert hierbei als CA-Komponente. SLEUTH simuliert das zukünftige städtische Wachstum auf Basis von historischen Landnutzungsdaten und spezifischen Wachstumskoeffizienten. Zur Erhöhung seiner Modellierungsfähigkeiten und zur Einbeziehung von elementaren Antriebskräften von *urban sprawl* wird SLEUTH erstmals mit Support Vector Machines kombiniert. Nachdem die Genauigkeit des CA erhöht worden ist, wird er mit ReHoSh (Residential Mobility and the Housing Market of Shrinking City Systems) gekoppelt. Das MAS ist speziell zur Modellierung von Bevölkerungsmigration, Wohnflächenpreisen und den Wohnraumbedarf in schrumpfenden Stadtregionen entwickelt worden. Die simulierten Dynamiken basieren auf Interaktionen zwischen verschiedenen Haushaltsgruppen und Entscheidungsträgern des Immobilienmarktes.

Im Zuge der Arbeit werden die Fragen nach den wichtigsten Antriebskräften von *urban sprawl*, seinen Wachstumsraten und Verortungen sowie die Fragen nach dem zukünftigen Umzugsverhalten der Haushaltstypen und der Immobilienpreisentwicklung des Ruhrgebietes als Beispiel einer polyzentrischen Schrumpfungsregion beantwortet. Die Ergebnisse von SLEUTH und ReHoSh werden zunächst lose gekoppelt und einer räumlichen Analyse unterzogen, in der die modellierten kommunalen Unterschiede der Wohnungsmarktentwicklung de-aggregiert werden. Im Anschluss wird ein Konzept

vorgestellt, auf Basis dessen SLEUTH und ReHoSh in einen Geosimulationsansatz integriert werden können. Diese Arbeit führt semi-explizite Gewichtungskarten als Möglichkeit ein, die Dynamiken von Siedlungsmustern und regionalen Wohnungsmärkten gleichzeitig zu erfassen. Der CA-MAS Modellverbund wird kalibriert, validiert und schlussendlich zur Szenarien-Simulation der städtischen Zukunft des Ruhrgebietes angewendet. Durch die Anwendung des Ansatzes in einer „digitalen Petrischale" werden zusätzlich die generischen Strukturelemente des *urban sprawl* im Ruhrgebiet ermittelt.

1 Introduction

1.1 Background of the Study

In his 1937 lecture on town planning, the American landscape designer EARLE DRAPER initiated a term describing the unaesthetic and uneconomic settlement structure of American cities. In reflecting the obliteration of rural and urban spaces, this term grew more and more in popularity: "perhaps diffusion is too kind of word ... in bursting its bounds, the city actually *sprawled* and made the countryside ugly, uneconomic [in terms] of services and doubtful social value" (WASSMER, 2002: 9). Ever since the term "sprawl" emerged in a geographical context, nearly 80 years have passed and the specific patterns and processes of growing cities have developed from an American to a European problem in general and a German problem in particular. Today, approximately 75 % of the European and German population live in urban areas (EEA, 2006; IT NRW, 2013; LAVALLE et al., 2002). While the population and job growth rates of most urban areas in Germany stagnate or even decrease in a relative and absolute meaning, the morphological growth of cities is ubiquitous (DOSCH & BECKMANN, 2001; HOYMANN et al., 2012; SIEDENTOP & FINA, 2010; SIEDENTOP, 2006). Accordingly, the land consumption, i.e. the conversion of open spaces to built-up land covers, is a constantly proceeding process spilling over the actual urban agglomeration borders and bequeathing a spatial footprint of sealed surfaces to the rural regions (Fig. 1.1). The biggest absolute amount of newly built-up areas appears in the agglomerations and their direct hinterland. Compared to their number of inhabitants those regions experience the highest relative increases of urban land uses and impervious surfaces (SIEDENTOP & KAUSCH, 2004). The same even holds true for the structurally weak regions in the eastern part of Germany as well as for the Ruhr in the western part struggling with urban shrinkage, a constant exodus of people and jobs in urban areas (COUCH et al., 2005; KABISCH et al., 2006).

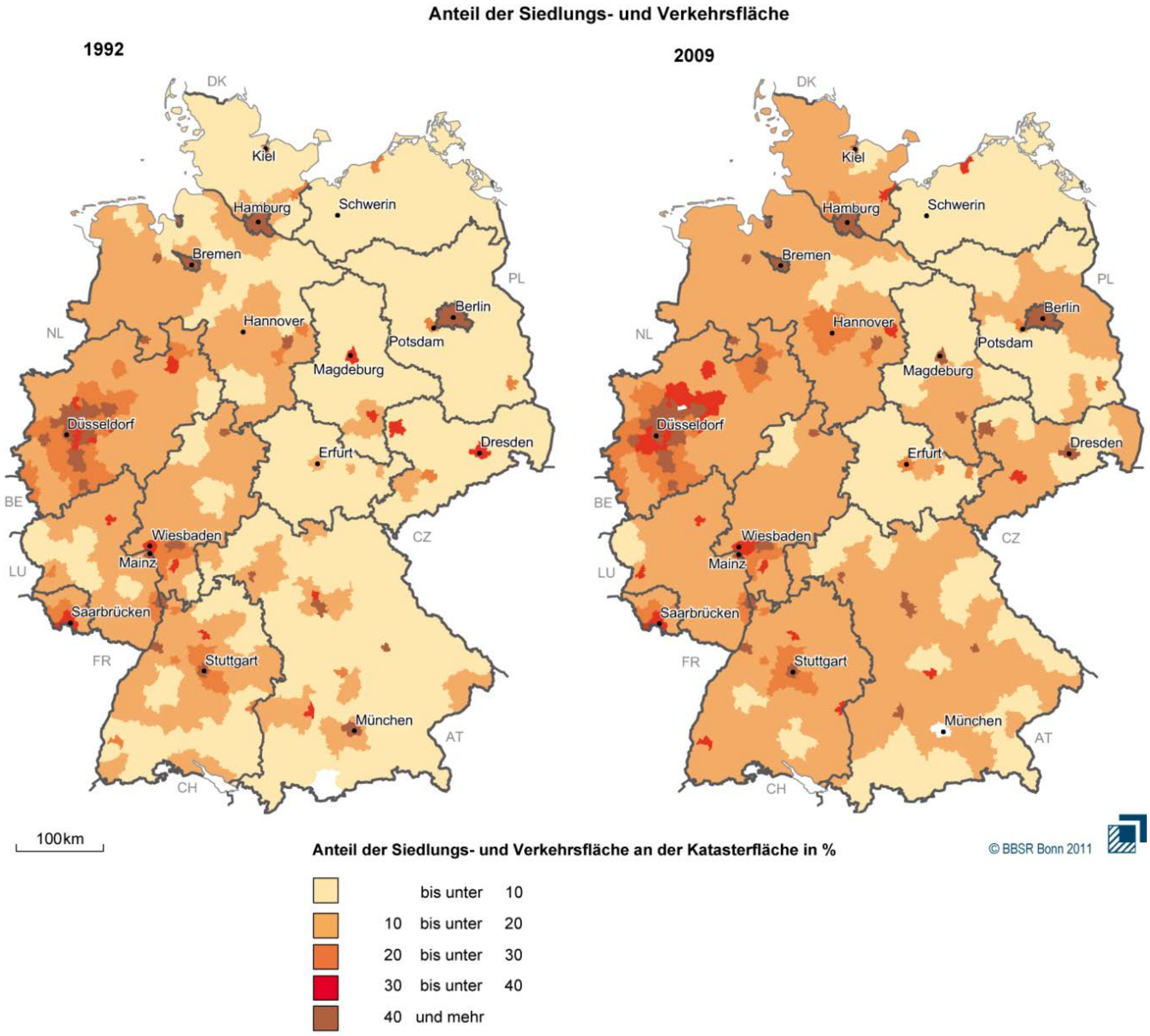

Figure 1.1. Spatial distribution and intensity of land consumption in Germany (Source: BECKMANN*, 2011).*

However, there is no consistent definition of "urban sprawl" (ANTROP 2004; EEA 2006; HOYMANN et al., 2012; LAVALLE et al., 2002; SIEDENTOP & FINA, 2010; SIEDENTOP, 2006) and neither is there an agreement on how to treat its causes, evaluate its effects, or measure its progress (MUNLV, 2013; RITTER, 2003; SIEDENTOP & FINA, 2010; VICENZOTTI, 2012). It seems that the quote "urban sprawl is like pornography: It is hard to define, but you know it when you see it" (CERVERO, 2000: 5) reflects quite well the difficult conceptual and analytical handling of urban sprawl and its implications. As the fragmentation of the landscape and the sealing of soils are nearly irreversible, the awareness of German decision makers and stakeholders in the fields of spatial planning and politics keeps rising. The current town planning principles should be guided by the paradigms of compact settlements, socio-ecological sustainability, decentralized concentration of people and jobs, as well as a functional through-mixing within the cities (HOYMANN et al., 2012; MUNLV, 2013). Ideas have been developed to establish an identity for the German *Zwischenstadt* (SIEVERTS, 2001). They try to characterize the archetypical manifestations of the rural-urban mash-up like satellite cities, bedroom communities, free- and highways, industrial facilities, office parks, specialty markets, as well as factory outlets and urban entertainment centers (UEC). On the one hand, those concepts facilitate a purposeful reconstruction, emphasize intraregional developments across community borders, and mediate rural-urban conflicts (VICENZOTTI, 2012). On the other hand, they are criticized due to their positive perception of urban sprawl and are suspected to enhance the deconcentration processes (HOYMANN et al., 2012; MUNLV, 2013; RITTER, 2003; SIEDENTOP & FINA, 2010; UMWELTBUNDESAMT, 2000). However, the Federal Government of Germany adopted a directive pursuing the reduction of daily land consumption from 130 ha in 2002 to 30 ha until 2020 (BUNDESREGIERUNG, 2002). Although the directive is stressed regularly and supported by projects like LAG 21 and "Allianz für die Fläche" as well as initial zoning laws (BUNDESREGIERUNG, 2004; LAG 21, 2008; MBWSV, 2013; MUNLV, 2009, 2013; MWEIMH, 2007), with a daily land consumption of 10 ha per day in the Federal State of North-Rhine Westphalia alone the "30-hectare goal" is not going to be reached (HOYMANN et al., 2012; MUNLV, 2013; SIEDENTOP & FINA, 2010).

Being one of the most challenging land-use and land-cover changes implicating several consequences for the anthropogenic and geobiophysical spheres, urban sprawl has become an inherent part of the international sustainability discourse in the context of global change (GLP, 2005; IPCC, 2012; MILLENIUM ECOSYSTEM ASSESSMENT, 2005; RAMANKUTTY et al., 2006; UNEP, 2012). The same holds true for geographical research with its long history of diverse theories and models of land-use change in general and urban sprawl in specific. Above all, those models try to simulate future patterns, predict growth rates, and understand the cause-effect relationships of driving forces. They can be distinguished by their thematic focus, executable scales of space and time, technical principles, ontological entities, potential utilizations, or epistemological interests. Extended reviews of urban land-use change models are given in BATTY (2008), BENENSON & TORRENS (2004), BRIASSOULIS (2000), BROWN et al. (2004), CLIFFORD (2008), GOETZKE (2012), HEROLD et al. (2001), HUNT et al. (2005), JUDEX (2008), MATTHEWS et al. (2007), POELMANS & VAN ROMPAEY (2010), PONTIUS et al. (2008), ROBINSON et al. (2007), ROUNSEVELL et al. (2014) SCHALDACH & PRIESS (2008), SCHWARZ et al. (2010), SCHWARZ & HAASE (2009), SILVA & WU (2012), PARKER et al. (2003), and WU & SILVA (2010).

One of the most important streams of urban models understands urban areas as complex systems exhibiting characteristics of non-linearity, irrationality, multilevel feedback loops as well as emergence phenomena. Those geosimulation techniques make use of artificial intelligence to model the micro processes being responsible for the macro pattern of urban systems (BATTY, 2005; BENENSON & TORRENS, 2004; COUCLELIS, 1989; MILLER et al., 2004, HUNT et al., 2004). Following the famous quote by Aristotle "the whole is more than the sum of its parts" they model urban systems in a bottom-up manner. Cellular automata (CA) and multi-agent systems (MAS) are very popular geosimulation tools. They stimulated the shift from aggregation to disaggregation, from homogeneity to heterogeneity, and from equilibrium to disequilibrium in urban modeling. While CA focus on neighborhood driven state changes, MAS primarily simulate behavior alterations of the system's actors. Because of their complementary principles they are regarded as perfect to be integrated into one modeling approach dealing with both: spatially explicit and implicit dynamics of urban sprawl. This thesis mainly aims to construct an integrate hybrid modeling approach using both AI techniques to geosimulate urban sprawl of the Ruhr. The performance of the urban CA SLEUTH will be enhanced and coupled with the MAS ReHoSh in order to reliably model the future urban pattern and housing market dynamics of the Ruhr. Before the structure, outline, and research questions of the thesis are presented, a brief overview of the implications of urban sprawl, the complexity of urban systems, and important urban models in geography, as well as an introduction into the geosimulation with CA and MAS is given.

1.2 Geosimulation of Urban Sprawl and the Challenge of Complexity

1.2.1 Urban Sprawl – Morphology and Effects

Urban sprawl is often treated as a specific of urbanization and urban growth. The classification of those processes is not homogenous and their definitions oscillate between the pure expansion of impervious surfaces and the distribution of urban activities and life styles in addition (ANTROP, 2004; EEA, 2006; HEINEBERG, 2014; HIRSCHLE & SCHÜRT, 2008; HOYMANN et al., 2012; LAG 21, 2008; SIEDENTOP & KAUSCH, 2004; SIEVERTS, 2001). The physical appearance of urban sprawl is defined by the European Environment Agency (EEA) as a low-density expansion of large urban areas under market conditions into the rural surroundings of agglomerations. They see it as patchy urban growth leaving leap-frogged areas (EEA, 2006). In order to get beyond the physical dimension of urban growth, the term urban sprawl should imply the selected aspects listed below:

- *Land consumption*: The conversion from non-urban to urban land cover and land uses for the main part indicating a certain amount of newly built-up, impervious areas (ULMER et al., 2007).
- *Deconcentration*: The spatial shift of population and jobs as well as other urban activities and functions from the cities' core centers via the suburban areas to the urban periphery and villages. In research literature it is also referred to as de-, ex- or counterurbanization (HEINEBERG, 2014).
- *Fragmentation*: The morphological change of former dense, compact, and monocentric settlements to a discontinuous, disperse, and polycentric structure. The radial-concentric mobility pattern is removed by a rather tangential-dendritic traffic relation (ANTROP, 2004).
- *Cross-planning*: The normative view in which the sprawling development of cities contradicts planning directives and political goals (SIEDENTOP & FINA, 2010).
- *Impacts*: The effects of urban sprawl affecting the coupled human-environment system with several social, economic, ecological, and cultural implications on different spatial and temporal scales (EEA, 2006; UMWELTBUNDESAMT, 2000).

The last point should be analyzed in more detail so that one can understand why scientists and planners do not only see a need for a theoretical definition but also for a practical monitoring of sprawling cities. The natural impacts of urban sprawl are manifold and concern several natural spheres. Cities consist by more than 50 % of impervious land cover (HOSTERT, 2007). The sealing of even fruitful and agricultural valuable soils leads to a loss of fertility, transformation, filtering, and buffering services (BLUM, 2001). The infiltration is disturbed and the surface runoff can be increased by five times with a sealing fracture of more than 90 % (ARNOLD & GIBBONS, 1996). Accordingly, the increasing risk of floods is accompanied by a reduction of the groundwater production and the evapotranspiration (ARNOLD & GIBBONS, 1996). The usage of those impervious surfaces with settlement, traffic or industrial purposes contaminate the water and the air. Thus, even more distant ecosystems can be polluted, oversalted, or alkalified by toxic substances like lead, hydrocarbon, and cadmium (BLUM, 2001). Pollution by noise and light as well as the fragmentation of habitats can banish animal species and reduce the biodiversity of a region (BLUM, 2001; GRILLMAYER et al., 2001; HAUGER, 2001). Here, the ecological footprint of a street can be estimated by two km and that of a European agglomeration by 1,000 times of its area (HAUGER, 2001; RAMANKUTTY et al., 2006). Again, the destruction of carbon sinks, the extension of heat islands and the intensification of traffic streams amplify the effects on climate change and global warming (DOSCH & BECKMANN, 2001; EEA, 2006).

Natural consequences mean consequences for the anthropogenic sphere. The polycentric urban structure raises the amount of car traffic by commuters. Congestions, dust pollutions, and noise stress can have impairments to health (SIEDENTOP, 2006; UMWELTBUNDESAMT, 2000; WOHLMEYER et al., 2001). Some studies investigated that the effects of recently built semi-detached houses in the sub- and exurbs as well as old housing estates in the surroundings of the core area can be demographic, ethnic, and socio-economic segregation (EEA, 2006; HEINEBERG, 2014; SIEDENTOP, 2006; UMWELTBUNDESAMT, 2000). Measurable financial impacts are a redistribution of commercial taxes and profits, which leads to commercial erosion of the core centers (HEINEBERG, 2014; RITTER, 2003; SIEDENTOP, 2006). Dispersed settlements increase the costs for the technical and social infrastructure (DOUBEK, 2001). Additionally, urban shadows can emerge showing a limited market access and an "urban implosion of space and time" (ANTROP, 2004: 16). Finally, the cultural landscape is nearly irretrievably changed by the reduction of recreational places (ANTROP, 2004; EEA, 2006; HOYMANN et al., 2012; RITTER, 2003). Thus, urban sprawl can be seen as a driver of the loss of the historic, cultural and aesthetic *genius loci*.

1.2.2 The Causes of Urban Sprawl and the Complexity of Urban Systems

For a long time, the natural increase of people and migration flows into the cities' core areas as well as the economic expansion of the industrial age constituted the most important factors responsible for the growth of German cities. During the last 50 years, however, the trends of land consumption and population growth have moved apart: While the German population has grown around one fifth, the amount of settlement and traffic areas has nearly doubled (HOYMANN et al., 2012; IT NRW, 2013). Accordingly, the natural and migratory demographic change must have been replaced by other factors driving urban sprawl. In research literature, the following aspects are mentioned regularly:

- *Economic wealth*: The individual economic status has steadily grown. The average household size increased from 15 m^2 in 1950 to 41 m^2 in 2000 (MIELKE & MÜNTER, 2008; RITTER, 2003). The persuasion of the wish for owning a house on greenfield sites amplifies the construction of new buildings. New supply types satisfy the changing product demand, diversify the product lines, and lead to an extensive land use by specialty markets and UECs (HEINEBERG, 2014; KLIJN, 2004; SIEVERTS, 2001).
- *Demographic change*: The German population is aging. While the baby-boomer generation retires and remains in their homestead, the birth rates of succeeding generations decrease and the amount of divorces increase. Moreover, the life styles of the German society pluralize so that the average household size has decreased from 2.3 (1990) to 2.1 (2004) persons per household and the number of one-person households has increased to one third (DITTRICH-WESBUER, et al., 2008; GEIST et al., 2006; GRÜBER-TÖPFER et al., 2008; MIELKE & MÜNTER, 2008).
- *Parish-pump politics*: While federal subventions for the creation of private residential buildings have been abolished, the price differential between cities and their hinterland is still evident. The fiscal competition of the communities to attract new inhabitants and companies causes a cutting of prices regarding industrial and commercial areas as well as the expansion of the traffic infrastructure. A more compact urban development is often exacerbated by a kind of NIMBY (not in my backyard) attitude of the stakeholders (GEIST et al., 2006; KISTENMACHER, 2001; KLIJN, 2004).
- *Dominance of the automobile*: The car orientation of German society is the cause and the effect of the aforementioned. It induces a loop of urban sprawl and traffic nodes which can perhaps be attenuated by a public and private re-orientation towards short-range transits (EEA, 2006; KISTENMACHER, 2001; KLIJN, 2004; SIEDENTOP, 2006).

Those causes build the main underlying driving forces of urban sprawl in Germany. But how do they interact? Which direct impacts do they evoke and what are their spatial outcomes? Why do they induce the emergence of sprawling urban areas even in regions affected by demographic and economic shrinkage? In order to measure, model, and understand urban sprawl, one has to think of it as a kind of urban land-use change embedded in the global land system (GEIST et al., 2006; VERBURG et al., 2004b). The changes of land uses and land covers and their driving factors construct non-linear, complex systems including irrational behavior of their human actors. COUCLELIS (1989: 142) sees the human driver of urban sprawl as a paradox where individual reasoned action backfires by disturbing the collective equilibrium and evokes a "non-zero-sum game". In line with the "prisoner's dilemma" and the "tragedy of the commons", she calls the low-density life style of residents and its responsibility of sprawled urban patterns the "Los Angeles Dilemma" (COUCLELIS, 1989: 142).

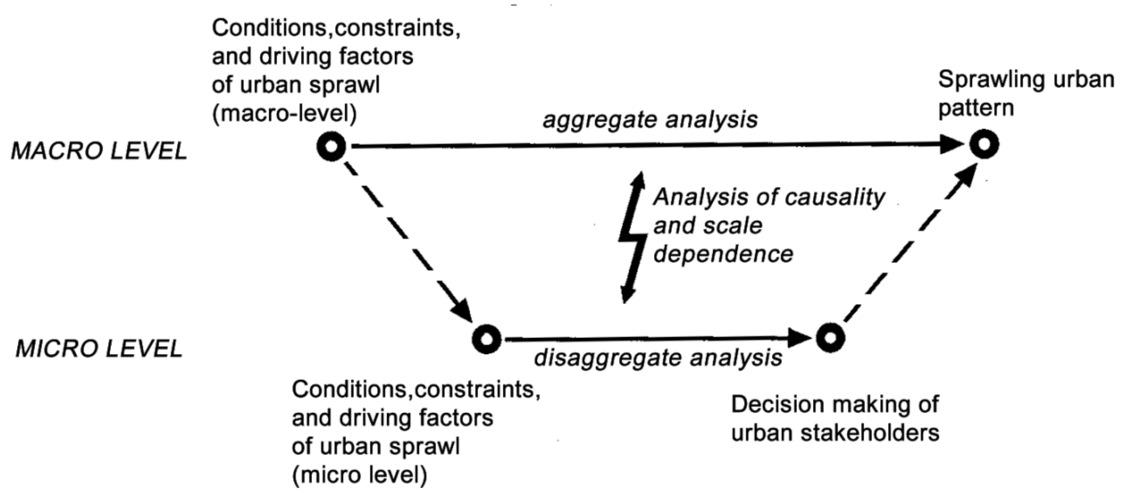

Figure 1.2. Representation of the linkage between micro-level and macro-level research in urban land-use change (edited according to VERBURG, 2006a).

Therefore, urban areas must be treated as open and dynamic systems in which macro level patterns are a result of behavioral driven processes of micro level actors (BATTY, 2005; GEIST et al., 2006; HAASE et al., 2010; KLIJN, 2004; RAMANKUTTY et al., 2006; SILVA, 2004; VELDKAMP & LAMBIN, 2001; VERBURG, 2006a) (Fig. 1.2). Accordingly, urban sprawl is a direct effect of the interaction and decision making processes of individuals as well as public and private stakeholders. Those interactions are performed continuously and simultaneously by decision makers showing an irrational and adaptive behavior. They change the states of the whole system and additionally react on those changes. Thus, urban systems reach a level of self-organization in which actors determine factors and reverse (HAASE et al., 2012). It is a horizontal and vertical interplay within and between organizational levels making the urban system elastic (GEIST et al., 2006). The social subsystems undergo a path dependant transition implicating their own structural transformation and that of their environment (GEIST et al., 2006). Perceiving and detecting those alterations, actors are able to modify their behavioral attitudes. This results in attenuating mechanisms ("negative feedback loop") reducing the speed and intensity of change. In contrast, amplifying mechanisms can also be initialized leading to an acceleration of degrading effects ("positive feedback loop"). In doing so, a clear distinction of what is significant cause and what is random correlation is very difficult (GEIST et al., 2006; KROLL & HAASE, 2010; LAMBIN et al., 2001; SILVA, 2004; VERBURG, 2006a; VERBURG, 2006b). The resilience of urban systems is not constant. At certain thresholds critical nodes are reached where internal or external influences known as unproblematic can have unpredictably higher impacts and determine the future trajectory of urban systems (BATTY et al., 2006; GEIST et al., 2006; SILVA & CLARKE, 2005). Those bifurcations illustrate that the cause-effect relationship of urban sprawl is neither linear nor unilateral. Urban systems cannot simply be explained by the equilibrium result of a certain set of driving forces.

They exhibit characteristics of hysteresis so that future developments and changes of urban systems are not only influenced by the current environment but also by the past one (ALCAMO et al., 2006; GEIST et al., 2006; LAMBIN et al., 2001; VERBURG, 2006a). The initial configuration of its states affects the future decision making of its actors. Exemplary, road expansions do not only improve the infrastructural development but also change the spatial pattern affecting the circulatory system of a region's economy and feeding back to road improvements (VERBURG, 2006b). Thus, the observation scales of time (1) and space (2) are fundamental elements for the analysis of urban systems: (1) Technological innovations or new policies are exogenous drivers and affect sprawling urban growth in a short-term. Due to co-evolutionary interaction between states and actors, they become endogenous and are affected by urban dynamics in a long-term (GEIST et al., 2006). (2) While on an aggregate level residential areas may be clustered resulting in a positive spatial autocorrelations, on an individual level a certain range of distance may be kept resulting in negative spatial autocorrelation (LESSCHEN et al., 2005; OVERMARS et al., 2003; VERBURG, 2006a; VERBURG et al., 2004a). Figure 1.3 demonstrates what happens if the rule of preserving a certain level of space in growing areas is applied to one single "urban cell".

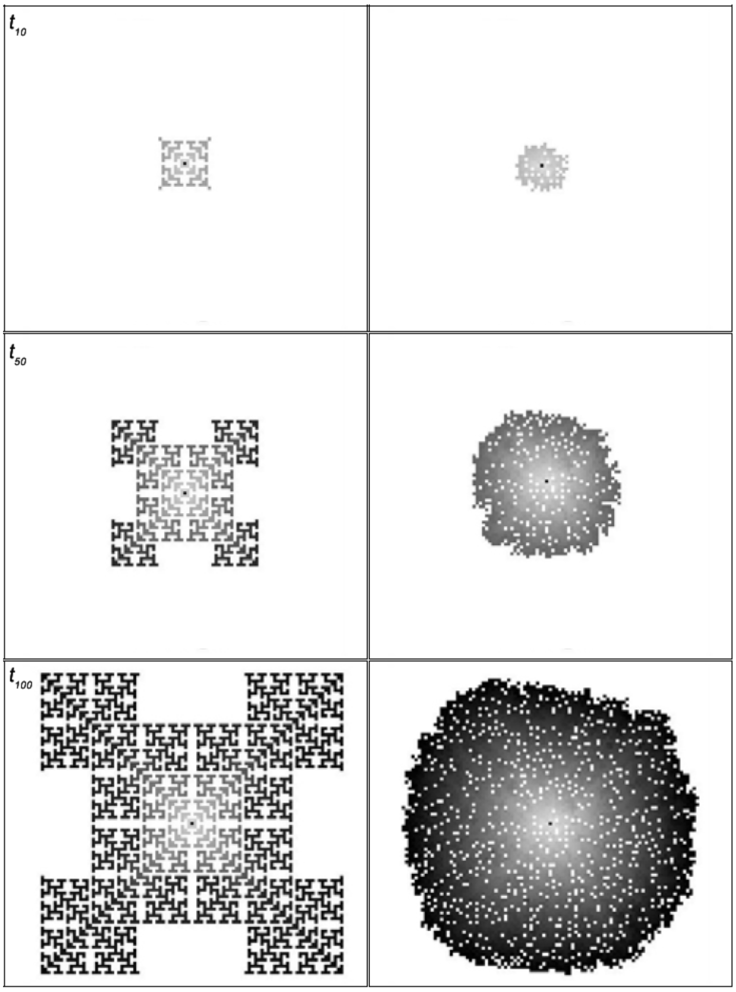

Figure 1.3. Deterministic and stochastic urban growth from the bottom up (Source: BATTY et al., 2006).

In the example of emergence, it is said that only those cells are allowed to be developed whose neighborhood does not comprise more than one "urban" cell. The result is an urban fractal with a self-similar pattern being "the same from near as from far" (GOUYET, 1996: 4). But what happens if the initial growth rule is relaxed and density or space does not really matter? The result is an amorphous mass and its emerging pattern is no longer reminiscent of idealistic Renaissance towns but of "plum pudding" (BATTY, 2005: 19). The transition of the urban system was disturbed; equilibrium became chaos. Hence, the atomic parts determine the future development of a system through their interaction within their environment. They need to be incorporated in integrated models of urban sprawl.

1.2.3 Modeling Urban Systems in Geography – A Brief History of Theories and Models

In order to clarify some important terms, a scientific theory should be defined as a logical system of thoughts describing and explaining processes and behaviors of real world phenomena. In contrast, a model should rather be seen as an idealized abstraction of reality approximating systems by simplification and mathematical relations. The computational implementation, application, and experimenting with a model should be understood as a simulation.

Geography is a science which is – owed to its main research subject: space – shaped by an interdisciplinary scientific tradition. Hence, theories and models dealing with the exploration of the structure and growth of cities have been incorporated into an economic, sociological, architectural, ecological, or political context (BRIASSOULIS, 2000). Certainly, the oldest theory is von Thünen's "Isoli[e]rter Staat" (THÜNEN, 1826) where land uses are put into a function of transport costs, land rent and probable yielded profit. The spatial results are the famous concentric rings around a city containing different land uses. His basic idea has influenced several economic oriented approaches like Alonso's urban land market theory in which the allocation of residential uses or commercial uses are dependent on the distance to the city centre (ALONSO, 1960). Other important micro-economic theories of urban land-use change are the least cost theory (WEBER, 1909), the central place theory (CHRISTALLER, 1933), and the theory of market webs (LÖSCH, 1940). They all allocate certain land uses in relation to their costs and every decision maker is thought of as a homo economicus. Another group of historic land-use models and theories of Geography are rooted in social sciences. Here, the Chicago School was the first stream of urban sociology. Its representatives developed ideas and concepts dealing with the functional and socio-economic structure and the expansion of North-Amercian cities. Theories like the concentric zone model (BURGESS et al., 1925), the sector model (HOYT, 1939), or the multiple nuclei model (HARRIS & ULLMAN, 1945) are shaped by terms like succession, segregation, invasion, and dispersion of residents.

Since the beginning of the computational age and the quantitative revolution after the Second World War, the basic nature of models has changed and the first urban simulation models have been developed in order to support spatial planning and system processes (BENENSON & TORRENS, 2004). They have tried to find the optimal settlement patterns as well as equilibrium distributions of land and its users. These models have conceptualized a monocentric structure of a city whose core area is orbited by urban activities on the periphery (MANDL, 2000; TORRENS, 2001). It was the first time when geography met general system theory. Those early models implemented the urban system as black box where input and output flows were balanced. Non-linear developments were integrated by using simple equations like logistic equations (BENENSON & TORRENS, 2004). A famous example is Lowry's model of metropolis which formalized the structure of an urban system for the first time (LOWRY, 1964). His equations are based on the idea of gravity models where spatial interactions in terms of trips are inversely proportional to their distances (HAYNES & FOTHERINGHAM, 1984). The results were promising and his model was applied to several cities (BENENSON & TORRENS, 2004). Another famous urban system simulation is Forrester's model of urban dynamics (FORRESTER, 1969). In contrast to Lowry, Forrester's model is non-spatial but focuses explicitly on the dynamic of urban processes. He firstly introduces feedback loops as important parts of urban systems determining the development of their labor and housing markets (BENENSON & TORRENS, 2004; TORRENS, 2001). Other urban simulation approaches of the 1960s and 1970s follow the tradition of statistical relations, econometric calculations, optimization as well as Forrester's system dynamic approach adapted for regional modeling (BENENSON & TORRENS, 2004; TIMMERMANS, 2003; TORRENS, 2001).

The exhaustive application of the simulation of urban systems reached a point where first critical voices were being raised. The most famous and harshest criticism was leveled by LEE (1973) with his "Requiem for Large-Scale Models". He listed seven sins in contemporary urban simulation which were hypercomprehensiveness, grossness, hungriness, wrongheadedness, complicatedness, expensiveness, and mechanicalness. While the last two can rather be waived nowadays, the other ones still can be regarded as important modeling guidelines with today's researchers often referring to them (GAZULIS & CLARKE, 2006; SILVA, 2004; TORRENS, 2001; WEGENER, 2009). In a nutshell, Lee proclaimed: keep it simple! This motto is still highly relevant today. One example of urban simulation models heeding that advice are Markov models. Based on the idea of Markov chains and stochastic, they estimate transition probabilities of land-use states of specific areas in a first step. In a second step, they put the observed entity and its transition probabilities dependent on the neighborhood (BENENSON & TORRENS, 2004; BRIASSOULIS, 2000). An example is Turner's spatial simulation model (TURNER, 1987). It belongs to a class of models which do not capture the processes and patterns of urban systems by deductively breaking it down but by inductively piercing together its atomic parts. Those models shifted the general simulation paradigm from "macro-statics to micro-dynamics" (BATTY, 2008: 1).

1.2.4 Geosimulation – Using the Artificial Intelligence of Cells and Agents

The new wave of urban simulation often goes under the name of geosimulation. MANDL (2000) defines geosimulation as a simulation where the modeled system processes, compartments, and applications are spatially characterized, and exhibit spatial relations. BENENSON & TORRENS (2004: 1) further comprehend geosimulation as "catch title that can be used to represent a very recent wave of research in geography … [which] is concerned with the design and construction of object-based high resolution spatial models … to explore ideas and hypotheses about how spatial systems operate". In order to distinguish geosimulation models from traditional urban simulation techniques, they characterize their spatial entities as discrete and nonmodifiable (e.g. cells or households), and the management of time as intuitively justified units (e.g. housing search cycles) (BENENSON & TORRENS, 2004). Thirdly, they understand interaction in geosimulation as the outcome of the behavior of elementary geographic objects changing over time (BENENSON et al., 2005; BENENSON & TORRENS, 2004; TORRENS, 2001). Individual behavior alteration substitutes flows between aggregated stocks so that geosimulation approaches model urban systems generatively from the bottom to the top. That upshot sounds quite familiar since it resembles the characteristic of microsimulation models and artificial intelligence (AI) solutions (AUGUST et al., 2001; COUCLELIS, 1989). Contrary to BENENSON & TORRENS (2004), the term geosimulation should not be overstressed and distinguished from microsimulation due to a lack of spatial objects, or from AI techniques due to a limitation of complexity behavior rules. In doing so, urban simulation tools like Waddell's UrbanSim (WADDELL, 2002) clearly dealing with compartments of urban systems would be excluded from geosimulation applications. Instead, both aforementioned definitions should be merged and urban geosimulation should be understood as microsimulation and the application of AI with the purpose of describing, explaining, predicting, or supporting spatial planning of (urban) land-use change processes and patterns.

The implementation of AI methods for urban simulation purposes were heavily influenced by technical progresses in terms of computation, land-use data acquisition, geographic information systems (GIS), complexity studies, as well as the development and use of AI approaches in natural and social sciences outside of geography (BENENSON & TORRENS, 2004; COUCLELIS, 1989; MILLER et al., 2004). Indeed, "geographers arrived somewhat late to the party" of addressing individual behavior alteration as design strategy of simulation applications (BENENSON & TORRENS, 2004: 19). First steps were made by HÄGERSTRAND and his approach to model the diffusion of innovation by incorporating individuals and the relevance of time (HÄGERSTRAND, 1967). But a broadened understanding of AI techniques as a solution to meet the complexity of cities first came up in the 1980s (BATTY, 2005; COUCLELIS, 1989, 2009; PARKER et al., 2003). The displacement of equations by code offered the possibility to explain the pattern and processes of complex open system dynamics on multiple organizational levels theoretically and experimentally (BETHELL, 2006). Hence, the research object of urban sprawl could leave the suggestions of order, stability, linearity, and rationality rooted in general system theory.

The two most important and most implemented geosimulation techniques in terms of urban systems simulation are Cellular Automata and Multi-Agent Systems. CA and MAS share the same roots but are very different in execution. One might say that CA are the very basic manifestation of MAS. The concept of AI in CA and MAS might be best described as soft or weak. In contrast to strong AI, acting as bases for machines that are very close to human intelligence, weak AI should be understood as a Turing-complete system in which entities exhibit the ability to apply and manipulate predetermined decision rules (BENENSON & TORRENS, 2004; WU & SILVA, 2010).

The invention of CA is attributed to the mathematicians VON NEUMANN (1951) and ULAM (1952), and "one can say that the "cellular" comes from ULAM and the "automata" comes from VON NEUMANN" (RUCKER, 1999: 69). The final breakthrough of CA came with JOHN CONWAY'S "The Game of Life" in 1970 (BATTY et al., 2006). Urban CA are often defined by (1) a raster lattice representing the spatial context, (2) a set of states associating a cell with a certain land-use type, (3) neighborhoods influencing the spatial configuration, and (4) transition rules regulating the conversion of a cell state with every (5) time step (BATTY, 2005; BENENSON et al., 2005; SILVA & CLARKE, 2005; SILVA, 2004, 2011; WU & SILVA, 2010). The experiment depicted in Figure 1.3 is a very simple example for an urban CA. The gridded two-dimensional character of a CA environment makes it well-suited for the simulation of urban land-use and land-cover conversion. Here, the most popular CA modeling urban growth were developed by BARREDO et al. (2003), BATTY & XIE (1997), CLARKE et al. (1997), HILFERINK & RIETVELD (1999), LANDIS (2001), TOBLER (1975), WHITE & ENGELEN (1993), and WU & YEH (1997). The progress of CA implementations profited heavily by innovations in remote sensing techniques (RAMANKUTTY et al., 2006). The world's radiances are recorded from a bird's eye view and stored regularly pixel-by-pixel. Hence, the world's surface is represented in a two-dimensional raster lattice facilitating a paradigm of modeling from the pixel. Natural or administrative borders are completely neglected so that land-use and land-cover patterns become the only things that matter. While maps always depend on a more or less subjective semiotics and imply reduced content, remotely sensed images provide the unmediated biophysical context of the coupled human-environment system. Additionally, remote sensing can provide measures for a number of environmental consequences (BARNSLEY et al., 2003; RINDFUSS & STERN, 1998). To give an example, by classifying a data set of radiances with the help of specific spectral characteristics, a continuous spatial texture is turned into a discrete spatial pattern. An overview of classification methods in the context of urban areas as well as their limitations is given in GRIFFITHS et al., (2010), HOSTERT (2007), and SCHNEIDER (2007).

In order to distinguish MAS from CA, the concepts of agency has to be investigated. While some studies differentiate between MAS and agent-based models (KOCH & MANDL, 2003; SCHWARZ & ERNST, 2009) both terminologies should be regarded as the same. However, there are several definitions of agents and agency in terms of geosimulation (BENENSON & TORRENS, 2004; KOCH, 2003; NARA & TORRENS, 2005; SILVA & WU, 2012; STEVEN et al., 2002; SUDHIRA et al., 2005; VALBUENA et al., 2008). In this thesis, an agent is defined as an abstract entity (e.g. household or community) which is autonomous, intelligent, mobile, and adaptive. Thus, an agent is able to communicate, to perceive his environment, to react to changes, to have an agenda, and to incorporate individual behavior. Here, an agent can be thought of as a kind of behavioral automata where the agent's characteristic of proactivity is the most important quality distinguishing the MAS from the CA. Proactivity refers to different goals like final aims, specific states, internal needs, as well as motivations, and/ or just maximization of selective rewards (BENENSON & TORRENS, 2004; COUCLELIS, 1989; LOIBL & TOETZER, 2003; MANDL, 2003). The paradigm of modeling from the people was pushed forward by the development in object-oriented programming (OOP). Contrary to procedural programming languages distinguishing between data and functions, OOP is characterized by encapsulation and polymorphism. It puts data and functions together into one closed class. Every instantiation of a class is associated with it. Thus, OOP is *eo ipso* suitable for achieving MAS modeling standards (BENENSON & TORRENS, 2004; STEVEN et al., 2002). MAS afford varied fields in order to simulate processes of urban systems. Their main focus lies on behavior alterations of individuals so that they are applied to modeling segregation (BATTY, 2005; SCHELLING, 2006), traffic behavior of pedestrians or cars (HESSE & RAUH, 2003; WAHLE et al., 2000), the relationships between companies and their clients (NAGEL et al., 2000), the simulation of planning situations (KOOMEN & BORSBOOM-VAN BEURDEN, 2011; HÄUSLER 2011; LIGMANN-ZIELINSKA & JANKOWSKI, 2007; MCINTOSH et al., 2008), as well as residential migration and search for housing (BANZHAF et al., 2007; BECKMANN et al., 2007; FONTAINE & ROUNSEVELL, 2009; HAASE et al., 2010; KABISCH et al., 2006; KROLL & HAASE, 2010; LAUF et al., 2012a; LIU et al., 2013; LOIBL & TOETZER, 2003; MOECKEL et al., 2007; WADDELL et al., 2008).

1.2.5 The Road to Hybrid Modeling in Urban Geosimulation

Table 1.1 sums up key features of both AI techniques. It shows that CA and MAS are complementary in terms of their focus, status change, mobility, and representations. The characterization also exhibits their limitations. The ability of both AI models to capture micro-level behavior alteration and human interactions transformed to macro-level urban land-use change – like urban sprawl – is approved. It has been examined in many studies that geosimulation tools are the right way to approximate the complexity challenges of urban systems and to avoid the ecological fallacy.

Table. 1.1. Key characteristics of CA and MAS (Source: WU & SILVA, 2010).

	CA	MAS
Focus	Regional or city level; Land conversion; Urban simulation	Households, abstract entities; Human action; Population dynamics
Status change	Determined by neighborhoods	Independent behavior alteration
Mobility	Immobile entities	Mobile entities
Representing	Spatial dynamics; Geographic factors	A-spatial dynamics; Socio-economic factors

However, it is the nature of modeling that every model incorporates disadvantages and limitations. Especially when run separately, the application of CA and MAS still have drawbacks. Several reviews describe the advantages and drawbacks of both geosimulation techniques (BATTY, 2005; BENENSON & TORRENS, 2004; MATTHEWS et al., 2007; SCHWARZ & HAASE, 2009; SILVA & WU, 2012; STEVEN et al., 2002; VERBURG, 2006a; WU & SILVA, 2010). Following Lee, many authors argue that MAS applications are getting more and more complex. They argue that methodology often drives the problem to be solved and not vice versa (LEE, 1973). In their critical reviews of geosimulation "From Macro to Micro – How Much Micro is too Much?" and "The Saga of Integrated Land Use-Transport Modeling: How Many More Dreams Before We Wake Up?" WEGENER (2011) and TIMMERMANS (2003) suggest that the irrationality of human actors dependent on their biophysical conditions, external influences, and variable over time and space is nearly impossible to capture in total. In contrast, the simplicity of transition rules in CA and their flexibility in terms of generalization allow nearly no insights into the processes of urban systems and resembles the first black-box-like approaches in urban simulations (BATTY, 2005; BENENSON & TORRENS, 2004; SUDHIRA et al., 2005; WU & SILVA, 2010).

According to those criticisms, the separation of simulation possibilities offered by CA and MAS makes it insufficient to depict the reality of urban systems (BENENSON & TORRENS, 2004; CLARKE, 2004; COUCLELIS, 2001; ROBINSON et al., 2007; SILVA & WU, 2012; TORRENS, 2001; VERBURG, 2006b; WEGENER, 2009, 2011; WU & SILVA, 2010). A need for hybrid systems following a holistic modeling paradigm for capturing both immobile and mobile entities is proposed. Otherwise, the missing link between the spheres of humans, land uses, and the environment would hamper the progress in urban geosimulation. The requirement of a stronger integration and coupling of both AI methods would also be sufficient regarding the multilateral integration of spatial pattern and non-spatial processes of urban systems into one modeling infrastructure (RAMANKUTTY et al., 2006; SCHWARZ & HAASE, 2009; SILVA & WU, 2012; VELDKAMP & LAMBIN, 2001; VERBURG, 2006b). Studies dealing with the creation of hybrid models often focus on specific change phenomena in urban systems like gentrification and segregation (BENENSON et al., 2005; NARA & TORRENS, 2005), suburbanization (LOIBL & TOETZER, 2003), rural-settlement development (LIU et al., 2013), transport systems (BECKMANN et al., 2007), spatial planning (LIGTENBERG et al., 2001), and urban expansion (SUDHIRA et al., 2005; ZHANG et al., 2010). Nevertheless, an integrated model incorporating urban sprawl prediction under demographic decline and economic shrinkage conditions has not yet been developed (LAUF et al., 2012b).

Many articles deal with the conceptualization and development of frameworks for the construction of an "ideal" integrated model of urban land-use change. The DPSIR-framework of the EEA is quite popular and orientates itself by the drivers, pressures, states, impacts, and responses within urban systems (EEA, 1999; WASCHER, 2004). Land-system scientists criticize that such frameworks follow the idea of "one-directional processes between driving factors and impacts" (VERBURG, 2006b: 1173). Instead, they address some important requirements of future urban geosimulation developments (GEIST et al., 2006; HUNT et al., 2005; MILLER et al., 2004; RINDFUSS et al., 2008; SCHWARZ & HAASE, 2009; SILVA & WU, 2012; VERBURG, 2006b):

- An urban system consists of a variety of physical elements, actors and processes.
- Markets are the basic organizing principle of an urban system.
- Representation of an urban system should focus on those elements that interact with the transportation system.
- Flows of people, goods, information, and money arise out of demand.
- Urban areas do not reach equilibrium.
- System time and space must be explicitly dealt with.
- Feedback between short-term and long-term processes has to be integrated.
- Interaction between multiple organizational levels of hierarchy needs to be addressed.
- Some activities arise in response to external influences.
- Some factors may be treated as exogenous for modeling purposes.
- A very detailed level of representation for actors and processes is necessary.
- Physical urban growth also occurs under conditions of demographic decline and economic shrinkage.

Another important aspect is the matter of calibration and validation. A consequent quantitative assessment of the degree of fit between simulation outcomes and real world states as well as the problem of stochastic variation is often neglected (RYKIEL, 1996; VERBURG, 2006a; WEGENER, 2011). Geosimulation developers are therefore encouraged to abide by "honesty in urban modeling" (CLARKE, 2004: 218).

The aforementioned modeling axioms close the introductory section dealing with the definition, causes, effects, complexity, and modeling challenges of urban sprawl. They build the guidelines of the following research objectives and the thesis outline.

1.3 Research Objectives and Thesis Outline

The main goal of the thesis is the geosimulation of future urban sprawl in the Ruhr in NRW (Germany). It is the first comprehensive study addressing simultaneously the settlement-pattern dynamics and the regional housing market dynamics of a polycentric German region. Hence, the thesis regards itself as substantial contribution to urban systems science in Germany in terms of its examination object as well as its technical challenge: It predicts key indicators of urban sprawl in shrinking regions by constructing a hybrid modeling approach based on the AI simulation techniques of CA and MAS. The CA and MAS are calibrated, validated, coupled, and finally implemented in order to simulate three different scenarios of changing housing preferences in the Ruhr.

A modified version of CLARKE'S Urban Growth Model (UGM) – better known as SLEUTH – will function as the CA component (CLARKE et al., 1997). SLEUTH is an abbreviation of its main input factors slope, land-use, exclusion, urban, transport, and hillshade. It has been applied in several urban growth studies all over the world (AERTS et al., 2003; AKIN et al., 2014; CHAUDHURI & CLARKE, 2013; CLARKE et al., 1997; DIETZEL & CLARKE, 2007; GAZULIS & CLARKE, 2006; GOETZKE, 2012; MAHINY & CLARKE, 2012; RAFIEE et al., 2009; SILVA & CLARKE, 2005; WU et al., 2008). Based on the input data and historic urban land-use information, the UGM models the physical urban expansion by accomplishing four simple growth rules with every modeling step. By using the modified version of UGM – consequently referred to as UGMr (Urban Growth Model reduced) – the thesis ties in with the study of GOETZKE (2012) who enhanced the calibration method of SLEUTH and recoded it into the JAVA-based modeling environment XULU (eXtendable Unified Land Use Modeling Platform) (SCHMITZ et al., 2007). As opposed to GOETZKE (2012) who focused exclusively on the spatially-explicit simulation of land-use pattern dynamics, this thesis will additionally integrate the spatially-implicit housing dynamics driving urban sprawl.

The use of UGMr induces a second goal of the thesis: the enhancement of the CA. The performance of UGMr for spatially explicit urban land-use simulation is very high but it allows no direct insight into the relationship between non-spatial human and ecological driving forces, spatial determining factors, and the emergence of urban sprawl. What is more, it contains a higher degree of stochastic variation leading to a simulation uncertainty which again weakens the ability of UGMr to allocate and quantify new urban cells. In order to enhance the simulation performance of the CA and to incorporate important driving forces of urban sprawl in NRW apart from population migration, UGMr is combined with a probability map of urban growth. The map is created by using another branch of AI: support vector machines (SVM). SVM is a machine learning algorithm based on statistical learning theory (BURGES, 1998; CORTES & VAPNIK, 1995; VAPNIK, 1995, 1998). The basic idea is to project input vectors on a higher-dimensional feature space, in which an optimal hyperplane can be constructed for classifying empirical data. SVM are well-established in land-use classification challenges showing very high accuracies (DRUCKER et al., 1999; GUO et al., 2005; MOUNTRAKIS et al., 2011; WASKE et al., 2010). Moreover, they are finding their way into land-use modeling applications (HUANG et al., 2010; OKWUASHI et al., 2009; XIE, 2006; YANG et al., 2008; ZHANG et al., 2003)

After UGMr is enhanced and guided by using SVM, the CA is coupled with the MAS ReHoSh. With ReHoSh (Residential Mobility and the Housing Market of Shrinking City Systems) a complex MAS is calibrated and implemented which simulates residential mobility and the housing market dynamics of shrinking regions. The MAS models population patterns, housing prices, and housing demand where all dynamics are based on multiple interactions between different household groups as well as stakeholders of the housing market. The model was originally developed by DIRK STENGER at the GIS research group of the Department of Geography, University of Bonn. Within the scope of this thesis and for the first time, ReHoSh has been calibrated, validated, and implemented in order to achieve a scenario-based prediction. After UGMr and ReHoSh are separately run, the concept of semi-explicit urban weights is introduced and implemented to transmit the results of ReHoSh to UGMr. Thus, it will be possible to transform the potential housing supply and demand as a result of individual decision making into a cellular environment.

The main study area which the hybrid CA-MAS geosimulation complex is set up for lies in the western part of Germany and in the central part of NRW: the Ruhr. With a polycentric and administratively fragmented structure but a homogenous and extensive urban area the Ruhr is a worldwide unique urban entity. In general, 11 cities and 4 districts form the biggest agglomeration (1,150 people p. km^2) in Germany, and with its 443,969 ha it is the fifth largest urban region in Europe. Concerning the geosimulation of urban systems, the Ruhr proves to be suitable due to two principal aspects: Firstly, it exhibits the highest absolute rates of urban sprawl in Germany. Between 1975 and 2005, the agglomeration grew around 37,022 ha with a total urban area of 94,990 to 132,012 (GOETZKE et al., 2006). Compared to other sprawling cities in Germany, the Ruhr's urban expansion can be described as a "metropolitan suburban sprawl" type with high values of new land consumption and with low fragmentations and dispersion patterns in the core area coexisting with lower densities and patched open spaces in the suburban area (SIEDENTOP & FINA, 2010). Secondly, the Ruhr acts as a "hero" in the scientific discourse of demographic decline and structural transformations in old industrialized cities. Like other members of the "rusty fellowship", the Ruhr has to struggle with archetypical problems of former mono-functional manufacturing cities depending on mining and heavy engineering: a demographic decline, an aging population, high unemployment rates, an incipient brain drain, and a lack of incentives to attract prosperous companies of the service sector, especially the "new economy" (BLOTEVOGEL, 2006; COUCH et al., 2005; DANIELZYK, 2006; GRÜBER-TÖPFER et al., 2008; KABISCH et al., 2006; SPIEGEL, 2004). Thus, the Ruhr offers a very good challenge to capture growing patterns and their relation to non-spatial dynamics regarding demographically and economically driven interactions of decision makers in an interregional urban housing market.

Aside from the Ruhr, the second study area is a transect of NRW comprising the commuter belt of the large cities along the Rhine valley (Cologne, Dusseldorf, Leverkusen, Neuss) in the western part and the hills of the "Bergisches Land" and "Siegerland" in the eastern part. In contrast to the Ruhr, the region shows both phenomena of urban sprawl: those types of cities experiencing a growing or at least stable population and economy and those sprawling under conditions of urban decline. Additionally, the region exhibits peripheral areas decoupled of central urban area functions and a stable urban pattern (GRÜBER-TÖPFER et al., 2008; MIELKE & MÜNTER, 2008).

The data pool of the thesis consists of remotely sensed land-use maps as well as zonal statistics and household characteristics. A time series of LANDSAT data of the years 1975, 1984, 2001, and 2005 is provided by the monitoring project NRWPro funded by the Ministry for Climate Protection, Environment, Agriculture, Nature Conservation and Consumer Protection of the State of North Rhine-Westphalia. The detailed classification process is presented by GOETZKE et al. (2006) and SCHOETTKER (2003). The international inter-comparable European Urban Atlas of the EEA serves as data base in order to associate land uses with potential dwelling areas on greenfields. The European Urban Atlas is part of the local component of the GMES/Copernicus land monitoring services (LAVALLE et al., 2002; MEIRICH, 2008). The Urban Atlas has a higher thematic resolution and is more land-use oriented than the NRWPro data sets which are rather based on the biophysical conditions of the surface than its anthropogenic valorization. Thus, the Urban Atlas provides additional spatially explicit information about urban land-uses like residential or industrial locations. The planning knowledge about the amount of potential residential areas on green- and brownfields in the cities and districts of the Ruhr is taken from RuhrFIS, a regional land-information system recently established for the whole Ruhr area (REGIONALVERBAND RUHR, 2011). Actual land values and real estate prices are taken from the information system of the NRW Expert Committee for Land Values (BORISPLUS.NRW, 2012). Other parameter inputs are derived from the State Office of Statistics (IT NRW, 2013). Based on those, dasymetric maps of potential driving forces of urban sprawl are created.

The hybrid model complex of CA, MAS and SVM not only allows direct insights into housing market processes as a main driver of urban sprawl but also considers socioeconomic and geophysical drivers. Additionally, the possibility to test the sensitivity of UGMr when coupled with other modeling techniques and when applied to different study areas can be tested. In a nutshell, the coupling of UGMr-SVM and ReHoSh is undertaken in order to answer the following research questions:

1. Can the performance of UGMr be enhanced by using an SVM-based probability map?
    a. Are SVM-based probability maps suitable to allocate urban growth and where are their limitations?
    b. How well do SVM perform in comparison to a standard technique like binomial logistic regression?
    c. How well do SVM guide UGMr and do they increase its modeling certainty?
2. Which driving factors influence the physical urban growth in NRW in general and in the Ruhr in particular and how do they take effect?
3. Where and at what rates will future land consumption in the Ruhr take place?
4. Where will households migrate and how will housing prices develop in the Ruhr?
5. Can the results of UGMr-SVM and ReHoSh be loosely coupled for a spatial analysis?
    a. How will future household densities in the Ruhr look like?
    b. What are the differences in the spatial distribution between household groups regarding their age and size?
    c. How will the development of prices for existent properties and newly developed housing differ regionally?

6. Is it possible to develop and formalize a concept in order to transfer the outcomes of individual decision making of interregional housing markets into a cellular environment?
7. Is the created concept of semi-explicit urban weights suitable to geosimulate different scenarios of the future urban sprawl in the Ruhr with an integrated hybrid CA-MAS model?
    a. Which quantitative and regional differences arise in the context of different dwelling types?
    b. How will the spatial dynamics of urban sprawl change dependent on behavior alteration by private and public stakeholders?
    c. What spatial differences emerge in an abstract environment with perfect constraints and fundamental urban structure elements?

For the first time, this thesis will introduce individual behavior-based decision making into the urban growth model SLEUTH. Again, it is the first time that the simulation performance of SLEUTH is enhanced with the integration of SVM. Thus, changes in future pattern dynamics in urban regions affected by processes of demographic decline and economic shrinkage can be reliably analyzed. The creation of semi-explicit urban weights as an innovative approach is conducted in order to construct a hybrid model of integrated geosimulation. Hence, spatially implicit urban processes of regional housing markets become a spatially explicit pattern of urban sprawl.

The research questions listed above are to be answered by using methods of remote sensing, GIS, machine learning, statistics, and AI. Figure 1.4 depicts a structured overview of the fundamental methods and models as well as software and data of the thesis.

Since it is a cumulative thesis, its three consecutive main sections have been submitted and published in three different internationally ranked journals. They all contain an own introduction and conclusion section. Subsequent to the current section, **Section 2** deals with the enhancement of UGMr by using SVM. Titled **"Supporting SLEUTH – Enhancing a Cellular Automaton with Support Vector Machines for Urban Growth Modeling"** (ANDREAS RIENOW & ROLAND GOETZKE), it has been published by the interdisciplinary journal **Computers, Environment and Urban Systems**. In the context of the thesis, it deals with research questions 1 and 2.

Section 3 comprises the contribution **"Geosimulation of Urban Growth and Demographic Decline in the Ruhr: a Case Study for 2025 using the Artificial Intelligence of Cells and Agents"** (ANDREAS RIENOW & DIRK STENGER). It has been published in 2014 at the **Journal of Geographical Systems,** which is dedicated to geographical information, analysis, theory, and decision making, and applies the enhanced CA UGMr-SVM and the MAS ReHoSh. The calibration and validation results of both are presented before they are implemented to the Ruhr. Being run separately, the results are loosely coupled with dasymetric mapping. Hence, the research questions 2, 3, 4, and 5 are being addressed.

“Sprawling Cities and Shrinking Regions – Forecasting Urban Growth in the Ruhr for 2025 by Coupling Cells and Agents” (ANDREAS Rienow, DIRK STENGER & GUNTER MENZ) closes the empirical part of the thesis. The paper has been published by **ERDKUNDE – Archive for Scientific Geography**. Accordingly, **Section 4** develops the concept of semi-explicit urban weights and couples UGMr-SVM and ReHoSh directly. Scenarios of different housing preferences are calculated by the MAS serving as input for the CA. The hybrid CA-MAS model is run and its results are analyzed quantitatively as well as with the implementation of a “digital petri dish” and the concept of urban DNA. The section deals with the research questions 6 and 7.

The final **Section 5** sums up all results and refers back to the drafted research questions. Additionally, it presents an outlook for further research in the context of integrated urban geosimulation.

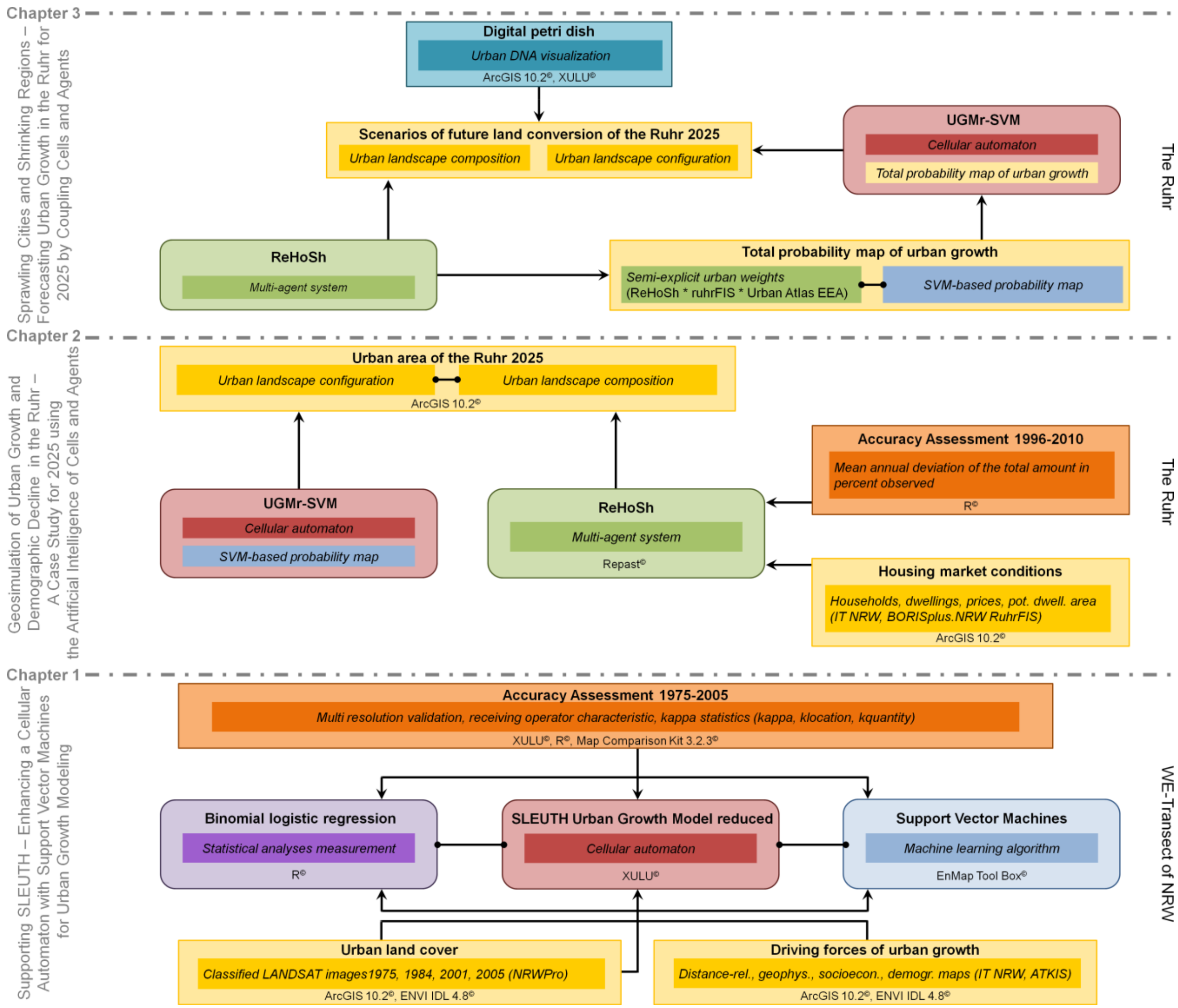

Figure 1.4. Structured overview of the thesis.

2 Supporting SLEUTH – Enhancing a Cellular Automaton with Support Vector Machines for Urban Growth Modeling

Source: RIENOW, A. & R. GOETZKE (2014): Supporting SLEUTH – Enhancing a Cellular Automaton with Support Vector Machines for Urban Growth Modeling. Computers, Environment and Urban Systems, doi: 10.1016j.compenvurbsys.2014.05.001

Abstract

In recent years, urbanization has been one of the most striking change processes in the socio-ecological system of Central Europe. Cellular automata (CA) are a popular and robust approach for the spatially explicit simulation of land-use and land-cover changes. The land-use change model SLEUTH, which is based on this technology, contains an urban growth model component and simulates urban growth using four simple but effective growth rules: spontaneous growth, edge growth, new spreading center growth, and road-influenced growth. Although the performance of SLEUTH for simulating urban growth is very high, the modeling process still is strongly influenced by stochastic decisions resulting in a variable pattern. Additionally, it gives no information about the human and ecological forces driving the local suitability of urban growth. The machine learning approach called support vector machines (SVM) is able to avoid this disadvantage. The basic idea is to project input vectors on a higher-dimensional feature space, in which an optimal hyperplane can be constructed for separating the data into two or more classes. By using a specific feature selection, important features can be identified and separated from unimportant ones. The objective of this research is therefore to combine the simulation skills of CA on the one hand and SVM on the other hand in order to achieve an integrated modeling approach which overcomes their specific drawbacks, but preserves their specific strengths. The anchor point for joining artificial intelligence and machine learning physique is the exclusion layer of SLEUTH. It will be replaced by an SVM-based probability map of urban growth. As a kind of litmus test, we compare the approach with the combination of CA and binomial logistic regression (BLR), a frequently used technique in urban growth studies. The integrated models are applied to a study region in the western part of Germany. The study area in the federal state of North Rhine-Westphalia involves a highly urbanized region along the Rhine valley (Cologne, Düsseldorf) and a rural, hilly region (Bergisches Land) with a dispersed settlement pattern. Various geophysical and socio-economic driving forces (like distance relations, elevation, soil conditions, demographics, job market data) are included, evaluated via a forward feature selection, and finally compared to the BLR outcome. The validation shows that the quantity and the allocation performance of SLEUTH are augmented clearly when coupling SLEUTH with a BLR- or SVM-based probability map. The combination enables the dynamical simulation of different growth types on the one hand as well as the analyses of various geophysical and socio-economic driving forces on the other hand. The SVM approach needs less variables than the BLR model and SVM-based probabilities exhibit a higher certainty compared to those derived by BLR. Interestingly, this certainty could not be transferred directly into SLEUTH though the stochastic variability is depressed.

2.1 Introduction

In recent years, urbanization has become one of the most striking change processes in the coupled human-environment system of Central Europe (ANTROP, 2004; SIEDENTOP, 2006). The quantitative and qualitative measurement, prediction, and evaluation of land-use dynamics – especially urban sprawl – have come to play a central role in land-system science (BROWN et al., 2004; LAMBIN & GEIST, 2006; VERBURG, 2006a). The creation of appropriate and adjusted models is challenged by the complexity of urban systems with their manifold self-organization processes, non-linear relationships, and emergent properties as well as feedback loops between different spatio-temporal scales and compartments. In this context, an increasing number of studies testing the use of artificial intelligence techniques for urban simulation have emerged recently (BATTY, 2005; BENENSON & TORRENS, 2004; SCHWARZ & HAASE, 2007; STEVEN et al., 2002; WU & SILVA, 2010).

Among these popular techniques are spatially explicit cellular automata (CA) like SLEUTH (CLARKE et al., 1997). SLEUTH is an acronym for its input data (Slope, Land use, Exclusion, Urban, Transportation, and Hillshade) and a purely growth-oriented model. As a bottom-up approach it is not dependent on intensive pre-studies about the general causes of urban growth in a study area or the location-specific driving forces (CLARKE et al., 1997). Based on the principles of neighborhood effects and spatial autocorrelation, the simulation rules are relatively simple. However, due to its ability to capture the complex emergence of urban patterns, SLEUTH has been applied in several urban growth studies all over the world (CHAUDHURI & CLARKE, 2013; CLARKE et al., 1997; RAFIEE et al., 2009; SILVA & CLARKE, 2005; WU et al., 2008). Although the performance of SLEUTH for simulating urban growth is very high, the modeling process is still strongly influenced by stochastic decisions resulting in a variable pattern (CHAUDHURI & CLARKE, 2013). Besides, it gives no information about the human and ecological forces driving the local suitability of urban growth.

The machine learning concept called support vector machines (SVM) (CORTES & VAPNIK, 1995) is able to avoid these disadvantages. SVM are used in a variety of applications for solving classification problems (DRUCKER et al., 1999, Mountrakis et al., 2011; Guo et al., 2005; WASKE et al., 2010) and for regression challenges (GESTEL et al., 2001; VERPLANCKE et al., 2008). In SVM explanatory variables are used to calculate the probability of e.g. a raster cell belonging to a specific class. As a basic idea, input vectors are projected on a higher-dimensional feature space in which an optimal hyperplane can be constructed for separating the input data into two or more classes. By using a specific feature selection, important features can be identified and separated from unimportant ones. Thus, it is possible to gain insights into characteristic features determining the separation process.

XIE (2006) implements SVM for general land-use change objectives and tests different modification possibilities. HUANG et al. (2010) extend the results of SVM for rural-urban simulation applications. A spatially explicit application with the purpose of dynamic modeling of urban growth is not performed and neither is a feature selection conducted to analyze the different impacts of the possible driving factors. YANG et al. (2008) and OKWUASHI et al. (2009) are combining SVM with CA-based approaches for modeling urban growth in a spatially explicit way. YANG et al. (2008) apply their model to Shenzen city, and OKWUASHI et al. (2009) to the Lekki area of Lagos. Both case studies obtain nonlinear transition rules for CA simulation of urban land-use dynamics but suppress the complementary advantages of SVM and CA. Here, urban growth is falsely directed so that the model seals beaches and aquacultures (YANG et al. 2008) or overestimates edge growth (OKWUASHI et al. 2009). In addition, the aforementioned studies examine almost only ordinary distance variables representing proximity and market access while other influences like the regional job market or demographic changes are not considered.

Hence, the objective of this research is to combine the simulation skills of SLEUTH and SVM. It will be achieved by using an SVM based probability map where geophysical and socio-economic forces drive the local suitability of urban growth (MOUNTRAKIS et al., 2011; WASKE et al., 2010). As a kind of litmus test, we compare the results with the combination of SLEUTH and binomial logistic regression (BLR) (LESSCHEN et al., 2005; VERBURG et al., 1999). The two research questions of this study are:

1. Can the performance of SLEUTH be enhanced by using an SVM-based probability map?
2. How well do SVM perform in comparison to the widely used BLR in an urban growth application?

The paper is structured as follows: Section 2.2 introduces the study area and the creation of the different input data sets. In section 2.3 we explain the applied models and the chosen methods for assessing their accuracy. Section 2.4 presents an analysis of the selected driving forces as well as the derived probability maps and discusses the validation results. Finally, section 2.5 provides a short conclusion and offers an outlook on future research.

2.2 Study Area and Data

2.2.1 Study Area

The study area covers the mid-western part of the German federal state of North-Rhine Westphalia (NRW). The population density is 523 people per km² (2012). About half of the state area is used agriculturally, and a quarter is forested. About 20 % of the total area is built-up land (residential and commercial areas as well as transport infrastructure; see IT NRW, 2013). Besides the historical roots in agriculture and forestry, NRW has a considerable industrial heritage. For more than 150 years large parts of the state have been shaped by coal mining, iron and steel, and textile industry. Today, nearly 75 % of the people are working in the service and trade sector and the industrial centers of the past have undergone severe structural changes.

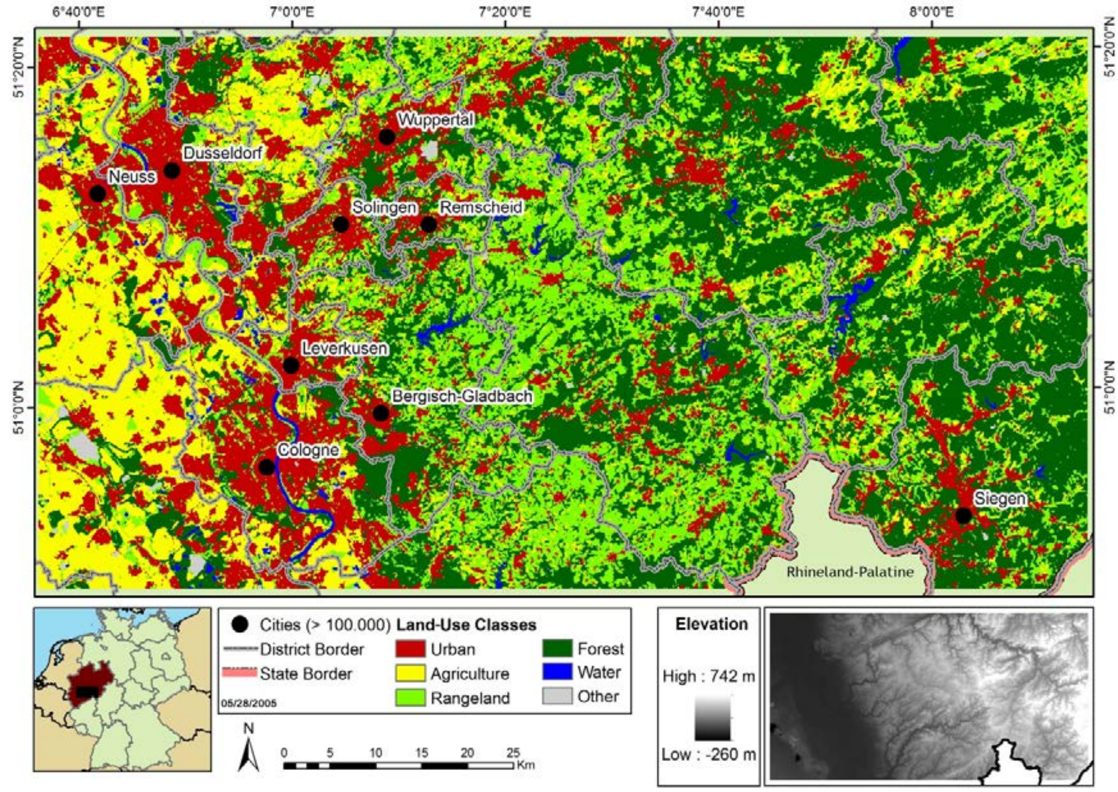

Figure 2.1. Land-use map and DEM of the research area in the southern part of North-Rhine Westphalia. The land-use map is based on classified Landsat-TM data acquired on 05/28/2005.

Our study area forms a transect covering the high diversity of the geographical and socio-economic variation as well as the different trends of land-use change in NRW (Fig. 2.1). The plains (~ 50 m a.s.l.) in the western part of the study area are dominated by intensive farming on fertile soils and high rates of urban expansion. This area belongs to the commuter belt of the large cities along the Rhine valley (Cologne, Düsseldorf, Leverkusen, Neuss), which are home to 2 million people. The south-western corner of the study area has been and is still formed by lignite mining. It is part of the "Rheinisches Braunkohlerevier", Europe's largest open pit mining area. The cities of Cologne and Düsseldorf are the largest cities of NRW and they are still increasing in population despite the current trend of the state. In the last decade, the population numbers in NRW decreased by 165,000 people, while these two cities gained 64,000 people. During the same period, the amount of settlement and transport infrastructure increased by more than 1,170 ha (IT NRW, 2013). Current research indicates that this trend will probably continue in the near future (BBSR, 2012). The study area as a whole gained 18,480 ha in urban areas between 1984 and 2001.

East of the large agglomerations of the Rhine valley, the terrain rises to the hills of the "Bergisches Land" (~ 500 m a.s.l.). The cities in the north-western part of this region have been important centers of the textile, machinery, and tool industry (Wuppertal, Solingen, and Remscheid). They faced structural difficulties after World War II and showed a decline in population of about 30,000 people in the last decade. Further south, the districts near Cologne are characterized by gentle hills, many scattered small villages as well as urbanized villages, a land use dominated by pastures, and an increasing population. The districts further east are of more rural character with large forested areas. They show a slight decrease in population numbers. The "Siegerland" in the south-eastern corner of the study area is densely wooded and has a tradition in iron mining and industry. In this area, the population numbers are decreasing as well.

2.2.2 Data

2.2.2.1 Land Use and Land Cover

The land-use data used in this study has been retrieved from a LANDSAT time series. On behalf of the Ministry of Environment, Nature Conservation, Agriculture and Consumer Protection of NRW, LANDSAT data of the years 1975, 1984, 2001, and 2005 have been classified in order to visualize problems related to land consumption. The classification procedure included a mixed approach of supervised classification and knowledge-based decision trees with a post-classification correction using the federal topographic information system ATKIS. The resulting classification product had a spatial resolution of 30x30 m and a thematic resolution of 12 land-use classes. Three urban land-cover classes have been distinguished based on their amount of impervious surface. The classification procedure (GOETZKE et al., 2006; SCHOETTKER, 2003) resulted in an overall accuracy of >85% for all four datasets taking all 12 initial land-use classes into account. After aggregating the classified datasets to binary maps showing only urban and non-urban areas, the overall accuracy increased to >94% for all four maps. The accuracy assessment for the 2001 and 2005 data was carried out using aerial images and ground truth information from a field campaign in 2002. For the 1975 and 1984 data visual interpretation combined with aerial images for sample areas were applied. Due to computational reasons, we rescaled the maps to a resolution of 100 m for this study. In 1975 (LANDSAT-MSS[1], acquisition date: 08/10/1975) 75,707 ha in our study area were classified as urban areas. In 1984 (LANDSAT-TM[2], acquisition date: 04/25/1984) the urban areas made up 107,455 ha, in 2001 (LANDSAT-ETM+[3], acquisition date: 05/05/2001) 125,935 ha, and in 2005 (LANDSAT-TM, acquisition date: 05/28/2005) 126,674 ha.

For the calibration of the CA models we took the urban land-cover data of 1984 as base year and of 2001 as reference year. For calibrating the BLR and SVM models we used urban growth detected in the classified LANDSAT data between 1984 and 2001 as dependent variables. For validation we used data from 1975 as base year and 2005 as reference year. Using these dates for validation instead of 1975-1984 or 2001-2005 has several advantages: Both datasets are independent and not part of the calibration process, they offer a large time span with a lot of change (which would not have been the case for

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[1] Multispectral Scanner (MSS).
[2] Thematic Mapper (TM).
[3] Enhanced Thematic Mapper (ETM+).

2001-2005), and it can be investigated, if the urban growth patterns the model has been calibrated to, hold true for the period before and after the calibration time span.

2.2.2.2 Pixels and People

Urban growth highly depends on local geophysical, demographic, and socio-economic conditions – the so-called driving forces of land-use change (VELDKAMP & LAMBIN, 2001). Therefore, we prepared a set of different maps of driving forces, including the geophysical parameters elevation and slope, as well as socio-economic and demographic variables based on recent empirical studies dealing with urban sprawl in Central Europe (ANTROP, 2004; SIEDENTOP, 2006).

For the majority of studies dealing with SVM in the context of urban growth modeling, ordinary distance variables representing proximity are used (HUANG et al., 2010; OKWUASHI et al., 2009; XIE, 2006; YANG et al., 2008). The effect those driving forces have on land-use decisions is in some cases based on accessibility. Therefore, we included accessibilities to “markets” or important infrastructure facilities by weighting the distances with the street network containing different road categories in order to indicate the car-centered mobility. By doing this, we created maps indicating the cost-weighted distance to airports, major cities and highway entrances. Other distance-related driving forces are not based on accessibility but on the mere proximity of landscape elements or infrastructure. Those have been included by calculating the Euclidian distance or a buffer.

The effect of other driving forces on urban growth is not based on accessibility or proximity. An example is the amount of population. But still, population is not equally distributed throughout the whole region. It is assumed that more people are living in the center of urban areas than at the fringe and that large urban patches are home to more people than small ones. Furthermore, areas without urban land use cannot be regarded as “unpopulated” since they are influenced by the ecological footprint of the human society (RAMANKUTTY et al., 2006). It can also be assumed that the urbanization probability is higher in regions close to densely populated areas than in regions far away from populated places. Those demographic and socioeconomic data being exclusively available on district level (IT NRW, 2013) have been disaggregated to dasymetric maps (LANGFORD & UNWIN, 1994). For population-related driving forces, we applied the following equation to weight the population in a district based on the sizes of the urban patches within the district:

$$P_{ij} = \frac{P_j}{A_j} \times A_{ij} \tag{2.1}$$

P_{ij}: population in an urban patch i in district j
P_j: population in district j
A_j: Area of all urban patches in district j
Aij: area of urban patch i in district j

For calculating population densities urban patches were derived from ATKIS (Table 2.1) and the population numbers mapped to a point location in the center of each patch.

Equation 2.1 was used to calculate the population for each point. Using a moving window with an arc radius of 10 km the population numbers were then distributed spatially. We have chosen a distance of 10 km because this approximates the average commuting distances in NRW (HULLMANN & CLOOS, 2002). For a more detailed discussion of the radius of activity and resulting locational profiles see HÄGERSTRAND (1967). By using a disaggregation method that distributes population data beyond the borders of urban patches, the pressure of population on neighboring regions can be represented in a map. For the other socioeconomic variables that are not population-related, inverse distance weighting was used to interpolate the statistical data that we projected to the central points of the different districts.

The variables used in this study describe the demographic, socioeconomic and geophysical conditions in the study area at the time we calibrated our model (1984-2001). As this is a comparative study and in order to keep things simple, we assume that these conditions and especially their effect for the probability of urban growth do not change over time. Otherwise the future development of these variables would have to be predicted in an economic model. Before using the variables in the BLR and SVM models, they have been checked for multicollinearity and highly correlated variables have been eliminated. Table 2.1 gives an overview of the selected driving forces.

Table 2.1. Variables selected for the BLR and SVM model.

Name	**Description**	**Source**	**Selected**	
			SVM*	**BLR****
Distance-related variables				
DistAirport	Cost-weighted distance (CWD) to next international airport (m*road category); Data range: 0 – 237,574 m	ATKIS***	8	$-1e^{-5}$
DistCity	CWD to next city > 25.000 inh. (m*road category); 0 – 102,944 m	ATKIS	7	$-8e^{-5}$
DistHighway	CWD to next highway exit (m*road category); 0 – 144,864 m	ATKIS	6	$-2e^{-5}$
DistRiver	Euclidian distance to next river; 0 – 22,983 m	ATKIS	1	$-4e^{-5}$
Geophysical variables				
Elevation	Elevation above sea level; -260 – 742 m	ATKIS Digital Elevation Model (DEM)	2	-.0012
Slope	Slope ; 0 – 97 percent	ATKIS (DEM)	n.i.****	-.0524
Socioeconomic variables				
LandPrice	Average land price in district 1990; Interpolation method: IDW; 57 – 522 Euro/m²	IT NRW	10	-.012
Unemployment	Unemployed per population 1991; IDW; 2.2 – 6.5 percent	IT NRW	9	-.5374

JobsSec	Number of jobs in secondary sector 1991; IDW; 27.5 – 107.5 T persons	IT NRW	3	-.0041
JobsTert	Number of jobs in tertiary sector 1991; IDW; 34.3 – 523.8 T persons	IT NRW	4	-.0039
Income	Average income per month in district 1991; IDW; 15,387 – 34,398 Euro/p	IT NRW	n.i.	$-5e^{-5}$
NetDwellArea	Per capita net dwelling area; IDW; 36.4 – 54.4 m²/p	IT NRW	5	.1089
ChangeNetDwell	Change in the per capita net dwelling area 1990-2001; IDW; -4.7 – 12.0 m²/p	IT NRW	n.i.	-.0413
Cars	Number of cars in district; DF (10 km kernel); 14 – 150 per 100 persons	IT NRW	n.i.	-.0776
Demographic variables				
PopDens84	Population density 1984; density function (DF, 10 km kernel); 49.1 – 3640.2 p/km²	IT NRW	11	-.0003
ChangePopDens 84-01	Change in population density between 1984 and 2001; DF (10 km kernel); -82.9 – 198.2 p/km²	IT NRW	n.i.	-.0035
Migration25-50	Difference between in- and out-migration per settlement (average between 1995 and 2001) of the group aged 25 to 50; DF (10 km kernel); -224.8 – 452.7 persons	IT NRW	n.i.	.0019

* Rank according to the forward feature selection.

**All variables selected for the BLR models achieved a significance level of 0.95 or more. The column includes the estimated regression coefficients. The intercept is 9.7876.

*** ATKIS: Amtliches Topographisch-Kartographisches Informationssystem (German federal topographic information system). Source: Arbeitsgemeinschaft der Vermessungsverwaltungen der Länder der Bundesrepublik Deutschland (AdV).

****not included

2.3 Methods

The described land-use data and driving forces of urban growth constitute the main input to train the BLR and the SVM model. Subsequently, the probability maps (prob. Map) of the constructed models are used to enhance the performance of the CA SLEUTH. Figure 2.2 visualizes the workflow including the data and methods used in the study.

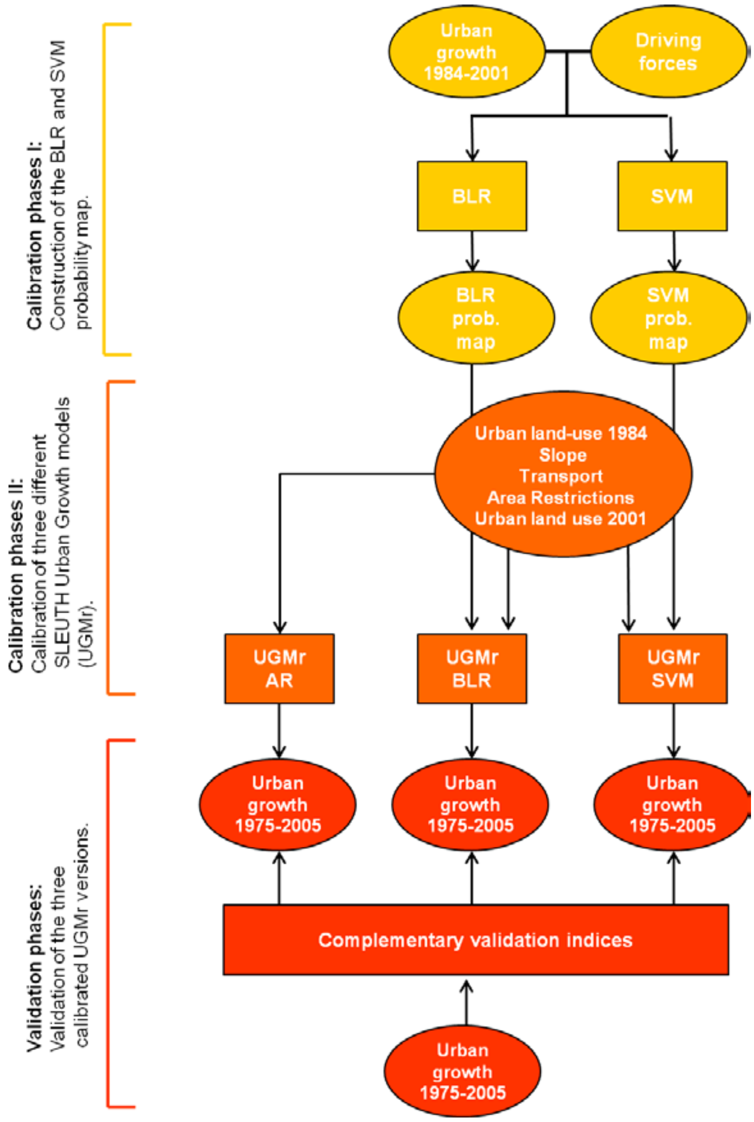

Figure 2.2. Workflow including the data and methods used in this study.

A short overview of the theoretical and mathematical background of BLR and SVM will be given. Afterwards, the simulation principles of SLEUTH and the applied accuracy assessment techniques are to be explained.

The starting point for building the BLR and SVM model is a scenario of separating a set of training vectors T belonging to two classes

$$T = \{(x_i, y_i): i = 1, \dots, n\}\ x_i \in \mathbb{R}^n, y_i \in \{-1,1\} \tag{2.2}$$

where y_i is the class label, in our case urban growth and non-urban growth, and x_i is a data point in the n-dimensional feature space. Here, the dimension of the input space is determined by the range of driving forces of urban growth. To avoid spatial autocorrelation, a stratified sampling method was applied (CONGALTON, 1991; XIE, 2006) to generate a training data set containing 4,000 pixels of urban growth and non-urban growth each and a minimum distance between equal pixels of 1 km.

2.3.1 Binomial Logistic Regression

BLR is a common technique for creating probability maps as a spatially explicit prediction for the appearance of land-use classes (JUDEX, 2008; OREKAN, 2007; VERBURG et al., 2002; XIE, 2006). While linear regression models provide a quantitative explanation of the relation between a continuous response variable and one or more explanatory variables, BLR models estimate the probability of appearance of a discrete response variable. Here, it is the binary decision whether a pixel belongs to the urban growth class or not. The function of a BLR model is

$$P(y = 1 \mid x) = \pi = \frac{e^{\alpha+\langle\beta,x\rangle}}{1 + e^{\alpha+\langle\beta,x\rangle}} \tag{2.3}$$

The probability π of the response variable y dependent on the explanatory variable x is explained by $P(y=1 \mid x)$. The regression coefficient is $\beta= (\beta_1,\ldots,\beta_n)$ and the intercept is a. By rearranging equation 2.3 we get

$$\frac{\pi}{1 - \pi} = e^{\alpha+\langle\beta,x\rangle} \tag{2.4}$$

where the dependent variable is the ratio of probability and converse probability, i.e. the odds. With the logarithm of equation 2.4, the odds get linear dependent on x

$$ln\left(\frac{\pi}{1 - \pi}\right) = \alpha + \langle\beta, x\rangle \tag{2.5}$$

The logit (2.4), the probability (2.2), and the odds (2.3) of π are just three different ways to describe the same thing. While equation 2.4 may be the most comprehensible one, the logit model is, mathematically, the easiest one for analyzing the binary problem (MENARD, 2001).

2.3.2 Support Vector Machines

In their contemporary form, SVM were firstly outlined by CORTES & VAPNIK (1995). Along with artificial neural networks and genetic programming, they represent a new generation of machine learning algorithms. To put it simply, SVM are a linear binary classifier that labels a sample of empirical data by constructing the optimal separating hyperplane. Traditional machine learning methods try to minimize the empirical training error so that they tend to overfit (VAPNIK, 1998; XIE, 2006). They are strongly tailored to the training data, so transferring them to further data turns out to be difficult. According to the principles of structural risk minimization (VAPNIK, 1995, 1998), SVM try to minimize the upper bound of the expected generalization error through maximizing the margin between the separating hyperplane and the data (Fig. 2.3, left). The margin concept is the key element in the SVM approach for it is an indicator of its generalization capability (BURGES, 1998; HUANG et al., 2010).

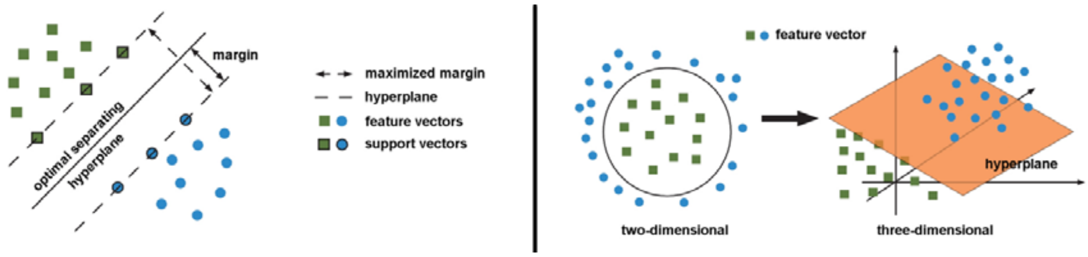

Figure 2.3. An optimal hyperplane constructed by the support vectors separates the training data (left). To solve a non-linear classification problem, the input data is projected onto a higher-dimensional Hilbert space (right) (Source: VOGEL 2013).

The main advantage of SVM is the option to transform the model in order to solve a non-linear classification problem without any prior knowledge. This separates SVM from BLR where you have to make valid assumptions regarding the possible non-linear relations between the variables (e.g. quadratic, exponential or polynomial) before transforming the model non-linearly. Using the so-called "kernel trick" (Eq. 2.12 & 2.13), the input vectors are re-projected to a higher-dimensional space in which they can be classified linearly (Fig. 2.3, right).

Considering the scenario of a set of training vectors *T* (1), we need to find a hyperplane which separates the positive from the negative feature vectors. The "separating hyperplane" *H* can be parameterized linearly by *w* and *b*

$$H: \langle w, x \rangle + b = 0 \qquad (2.6)$$

where *w*, element of R^d, is a normal to *H*, and *b*, element of *R*, the bias. The classification problem can be formalized as the decision function

$$sgn(f_{(x)}) = sgn(\langle w, x \rangle + b) \qquad (2.7)$$

For the linearly separable case we can define two hyperplanes H_+ and H_- constructed by the closest positive, resp. negative examples – the so-called support vectors:

$$\begin{aligned} H_+&: \langle w, x \rangle + b = 1 \\ H_-&: \langle w, x \rangle + b = -1 \end{aligned} \qquad (2.8)$$

Note that H_+ and H_- are parallel because they have the same normal and no training points fall between them. Through the perpendicular distances from the origin of H_+ and H_- it can be shown that the distance between the optimal separating hyperplane H_+ and *H*, resp. *H*- and *H*, is $1/||w||$' where $||w||$ is the Euclidean norm of *w*. So, the margin between H_+ and H_- is $2/||w||$. The optimal separating hyperplane can be found where the margin between H_+ and H_- is the largest. Hence, $||w||$ has to be minimized. The formulation of the constrained optimization problem is

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i$$
$$subject\ to\ y_i(\langle w, x_i\rangle + b) - 1 \geq 0\ for\ i = 1, \dots, n \tag{2.9}$$

The constant C is called penalty parameter and ξ_i is a slack variable representing the error in the classification. The first part of the objective function tries to maximize the margin between the two classes and the second part minimizes the classification error. The optimization problem is solved by formulating it in a dual form derived by constructing a Lagrange function according to the Karush-Kuhn-Tucker optimality condition (BURGES, 1998). The resulting classification rule is

$$sgn(f_{(x)}) = sgn\left[\sum_{i=1}^{n} \alpha_i y_i(\langle x_i, x\rangle + b)\right] \tag{2.10}$$

where a_i are the corresponding Lagrange multipliers to x_i and b is the constant. The support vectors are all x_i where $a_i \neq 0$.

If the classification problem is not separable linearly one cannot solve the decision function with the separation approach explained so far. The data set has to be transferred or projected respectively into a higher dimension: the Hilbert space. It extends the methods of vector algebra from two/three-dimensional spaces to spaces depicting any finite or infinite number of dimensions (Fig. 2.3). By using the function ϕ with $d_1 < d_2$ the amount of possible linear separations is increased:

$$\mathbb{R}^{d1} \rightarrow \mathbb{R}^{d2}, x \rightarrow \Phi_{(x)} \tag{2.11}$$

SVM are well-suited for the operation since the training data x_i emerge only in scalar products in terms of the optimization problem. The scalar product x_i, x is calculated in the higher dimensional space $\phi_{(xi)}$, $\phi_{(x)}$. The transfer is performed with the use of a kernel function k according to Mercer's theorem (BURGES, 1998):

$$k_{(x_i, x)} = \langle \Phi_{(x_i)}, \Phi_{(x)}\rangle \tag{2.12}$$

The Gaussian radial basis function kernel is a reasonable first choice (WASKE et al., 2010, XIE, 2006):

$$k_{(x_i,x)} = e^{-\gamma|x-x_i|^2} \tag{2.13}$$

The parameter *y* defines the width of the Gaussian kernel function. After the kernel trick the hyper plane can be set in a Hilbert space and the decision function becomes

$$sgnf_{(x)} = sgn\left[\sum_{i=1}^{n} \alpha_i y_i k(\langle x_i, x\rangle + b)\right] \tag{2.14}$$

Instead of predicting the label directly, the class probability is calculated (2.12) delivering the basis for the probability maps of urban growth. PLATT (1999) approximates the probabilities for binary SVM using a sigmoid function

$$P(y = 1 \mid x) = \frac{1}{1 + e^{A+f_{(x)}B}} \tag{2.15}$$

where *A* and *B* are parameters estimated by minimizing the negative log-likelihood function (PLATT, 1999; WU et al., 2004). Now it is possible to create a probability layer based on the principles of SVM and we can compare it with the probability layer based on BLR analysis.

For the construction of the SVM model we have chosen the software tool imageSVM® implemented in the EnMAP Toolbox® developed at the Humboldt University of Berlin. Originally, imageSVM was created for solving classification problems in the context of multi- and hyperspectral satellite imagery (WASKE et al., 2010). The output of an SVM classification with imageSVM is not only a classified binary image but also a probability image based on the principles of equation 2.15. The crucial step for constructing an SVM model is the search for the right parameter settings, including good values for the penalty parameter *C* (2.8) and the kernel parameter *y* defining the width of the RBF kernel (2.12). One method adjusting the counterbalance of the accuracy results of "known" training and "unknown" testing data is the *n*-fold cross validation procedure (HSU et al., 2010). According to the curse of dimensionality and the Hughes phenomenon, which describes the degradation of the classifier performance when increasing the number of features, it is additionally advisable to select the best feature combination (HUGHES 1968). A selection of the relevant features can improve the prediction ability, the generalization performance, and the computational efficiency of an SVM model (NGUYEN & DE LA TORRE 2010; MEWES 2011). In our case, a feature selection can additionally give some insights into the impacts of the different forces driving the local suitability of urban growth (cf. 2.4.2). A common procedure of SVM feature selection is a forward feature selection (HSU et al., 2010; WASKE et al., 2010). It initially trains each feature of the input feature set. The best performing feature is selected. The remaining features are used for training but in combination with the initially selected one. The procedure is repeated until all features have been selected. The result is a ranking of the different feature combinations. The features which weaken the SVM classifier can be eliminated.

2.3.3 SLEUTH – An Urban Cellular Automaton

The cellular automaton SLEUTH was developed by CLARKE et al. (1997) for land-use change modeling. Originally conceived for more than one land-use class, the majority of studies documented in the scientific literature identifies SLEUTH with one of its two sub-models: the Clarke Urban Growth Model (UGM) (CLARKE et al., 1997). UGM focuses on the simulation of urban growth exclusively (GOETZKE, 2012; HEROLD et al.2001 RAFIEE et al., 2009, 2009; SILVA & CLARKE, 2005; WU et al., 2008). The other SLEUTH component, the Land Cover Deltatron Model, is not used in this study.

For many applications, the quantity of data needed to calibrate UGM is difficult to acquire. It was therefore re-programmed by GOETZKE (2012) and implemented into XULU© (eXtendable Unified Land Use Modeling Platform), a JAVA-based modeling environment developed at the University of Bonn (GOETZKE, 2012; JUDEX, 2008; SCHMITZ et al., 2005).

The standard calibration evaluation method of UGM has been replaced by the multiple resolution validation (MRV) (PONTIUS et al. 2004; PONTIUS & MALIZIA, 2004). The MRV compares an observed simulated map with a validation map at different spatial resolutions. High resolutions are weighted more than low resolutions. The basic idea behind MRV is to attenuate the impact of localization errors by extending the conventional cell-by-cell comparison and considering the similarity of the whole neighborhood of a cell. Thus, the fuzziness of categorical maps is addressed (COSTANZA & MAXWELL, 1991; VISSER, 2004), which means that spatial patterns could be simulated quite perfectly by classifying only a few cells correctly. Additionally, urban land-use calibration with MRV only needs two maps; one of the starting year and the one of the final year of calibration. The modified version of the UGM is hereafter referred to as UGMr (Urban Growth Model reduced).

The base data consists of the urban land use expressed in the two classes "urban" and "non-urban" (cf. 2.2.2.1). Slope and data map of transportation infrastructure are mandatory for the model algorithm, while the exclusion layer is an optional component. It is used for incorporating political constraints like natural reserves or areas that are excluded for urban growth such as water bodies. Here, the binary exclusion layer (0 = growth possible, 1 = growth not possible) is combined with a probability map based on BLR and SVM techniques.

One growth cycle of UGMr represents one year of urban growth. Five growth coefficients (dispersion, breed, spread, slope, road gravity) define the four growth rules of UGMr subsequently performed for every growth cycle. (Fig. 2.4). The first growth rule is spontaneous growth (i), representing the random emergence of new urban areas. It is determined by the dispersion coefficient. Those newly urbanized cells can act as core areas for urbanization in their direct neighborhood (ii). UGMr also simulates extensive edge growth in a Moore neighborhood of at least three urbanized cells. The edge growth (iii) represents the radial urban sprawl and the infill of existing urban areas. It is regulated by the spread coefficient. The fourth growth rule is road-influenced growth (iv). Starting from a cell urbanized during the current growth cycle, the next road in a certain neighborhood is selected and a temporary cell is relocated along the road to its final position which is influenced by the dispersion coefficient. Each probable new urban cell selected by a growth rule is tested against the local slope and exclusion information before it will finally be urbanized. Here, the BLR and SVM probability maps direct the newly urbanized cells; especially those selected by the spontaneous growth rule.

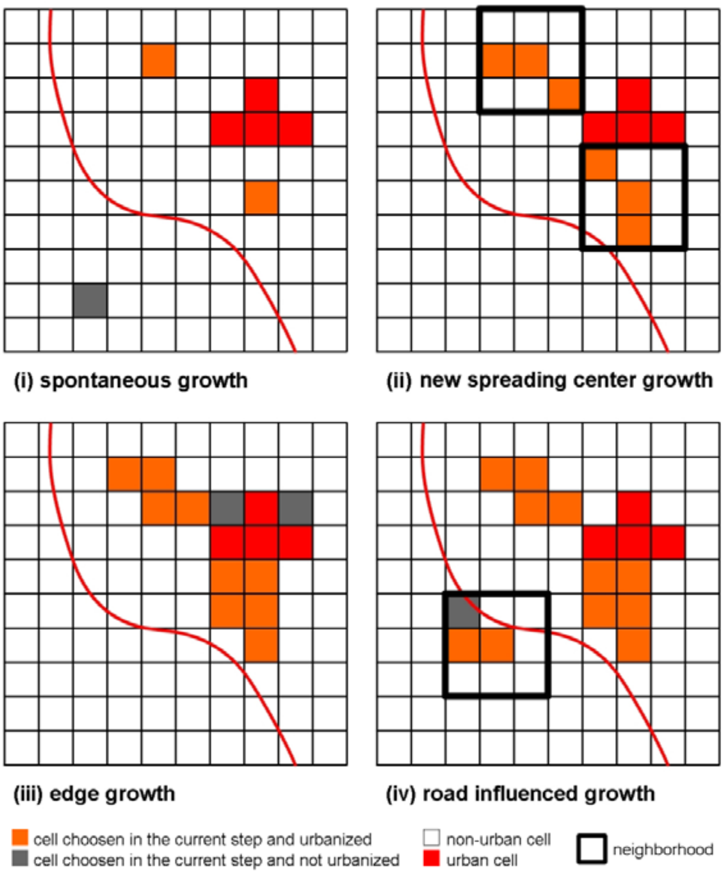

Figure 2.4. Growth types of a growth cycle in UGMr.

An urban CA is a typical bottom-up approach and tries to capture the self-organizing nature of complex urban systems (BATTY, 2005; BENENSON & TORRENS, 2004). No *ex ante* knowledge about the parameters is needed. They are detected inductively during model calibration. Hence, the calibration process is based on the brute-force method. Every combination of the particular growth coefficients between values of 0 to 100 is tested. Since an assessment of all possible parameter combinations would be far too time-consuming, the calibration procedure is performed in several steps, starting with a coarse evaluation and refining the results in several intervals (GOETZKE, 2012; RAFIEE et al., 2009; WU et al., 2008). Afterwards, the combination achieving the best MRV results is chosen. For the simulation run itself, 100 Monte Carlo (MC) iterations are used to depress the model's stochastic nature. The result of the MC iterations is a raster showing in every cell how often the model chose it for urbanization. By using a cut-off value (cf. 2.4.4), the map can be transformed into a binary land-use map (VERBURG, 2006a). A proved method for finding the best cut-off is the histogram frequency method (GOETZKE 2012, RAFIEE et al., 2009; WU et al., 2008).

2.3.4 Accuracy Assessment

To assess the accuracy of UGMr and compare its different model set-ups, we have chosen three different validation indices varying in their technical approach and their focus on evaluation: (1) The MRV with a "null model" comparison, (2) the receiving operator characteristic (ROC), and (3) Cohen's Kappa. In the MRV a simulation map is compared with a so-called "null model" – a map containing the initial land-use pattern which can be considered as a map of mere persistence (PONTIUS et al., 2008; PONTIUS & MALIZIA, 2004; VISSER, 2004). The resolution level where the agreement factor of the land-use model outperforms the null model for the first time is called "null resolution". The higher the null resolution, the better the land-use model performs.

The ROC is an approved index for the accuracy assessment of binary categorical probability estimations (PONTIUS & SCHNEIDER, 2001). The ROC divides the probability outcomes into percentile groups from high to low probability and compares the individual probability groups with the cumulative real values. The ROC only considers the positive values estimated by the model, in our case all cells labeled as urban growth. To define the ROC, the true positive rate and the false positive rate for every percentile group are plotted. The result is a curve where the area under the curve (AUC) is the measure that represents the ROC statistic. If a model acts randomly, the curve will be a line through the origin with a slope of 1 and an AUC of 0.5. If a model acts perfectly, the AUC is 1. The ROC Method is also used as calibration method for the creation of the probability maps derived by the BLR and SVM approaches.

Cohen's Kappa ($\varkappa$) is an evaluation coefficient of the inter-rater agreement and a standard measure for accuracy assessment of remote sensing image classifications (CONGALTON, 1991; LANDIS & KOCH, 1977). It is thought to be more robust than simple overall agreements, because it takes into account the proportion of correctly classified pixels due to chance. There is no common agreement how $\varkappa$ results should be treated. Generally, most authors characterize a $\varkappa$ below 0.4 as poor, below 0.75 as "fair" to "good", and better than 0.75 as "excellent" (ALTMAN, 1990; FLEISS et al., 2004; LANDIS & KOCH, 1977). PONTIUS (2000) developed two variations of Cohen's Kappa tending to address errors of location with $\varkappa_{loc}$ and of quantification with $\varkappa_{histo}$ in categorical maps separately.

2.4 Results and Discussion

2.4.1 Probability Maps of Urban Growth

The driving forces presented in table 2.1 form the feature space (Eq. 2.2) and build the base of training the BLR and SVM models of urban growth between 1984 and 2001. The actual interests of our study are the resulting probability maps of urban growth where every cell exhibits a continuous value indicating its probability of being urbanized. For assessing the accuracy the ROC is used. Figure 2.5 contains the ROC curve of both models. The curve of the SVM model clearly reaches a stable level much earlier than the BLR curve, which increases more linearly and stagnates only at high percentile groups. The AUC values confirm the visual impression. With a value of 0.94, the SVM model achieves an outstanding performance for the AUC; the BLR model produces a value of 0.76, which is still respectably good. Several studies dealing with the challenge of land-use and land-cover classification have shown the efficiency and accuracy of SVM (MOUNTRAKIS et al., 2011; WASKE et al., 2010). Most of these studies use spectral bands of satellite imagery as input feature space. The high ROC shows that the same seems to hold true for a feature space constructed by driving forces.

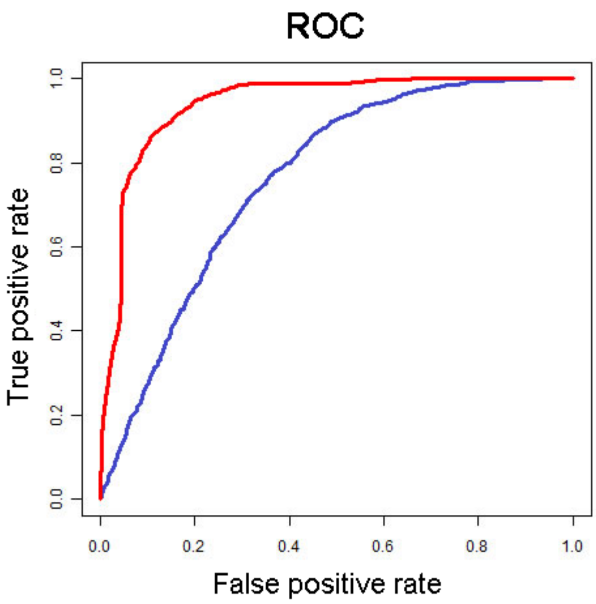

Figure 2.5. ROC curves of the BLR and SVM model.

The qualitative analysis of the probability maps at hand explains the reasons for the very different performances of the two models. Figure 2.6 shows the probability map based on the BLR (left) and SVM (right) model and a difference map created by subtracting both maps. Here, the cells with very high positive values represent high probabilities in the BLR but low probabilities in the SVM map; very high negative values represent low values in the BLR but high values in the SVM map. The three distance variables used in both models are much more influential than other variables. Hence, the transport network is distinctly depicted in both maps. The presence of a street increases the probability of adjacent urbanization. In contrast, areas in the rural Bergisches Land with high slope and elevation values are rather unlikely to undergo urban growth in the BLR map as well as in the SVM map. The main difference between both techniques is the handling of variables with high influence (LESSCHEN et al., 2005; WASKE et al., 2010; XIE 2006). Thus, high probabilities are assigned where urban growth is rather unlikely. The broad areas of high probabilities for urban growth at the edges of the Rhine agglomeration of Cologne and Düsseldorf in the BLR map underline this fact. It is even more obvious when compared to the SVM map where areas of high probability are more differentiated.

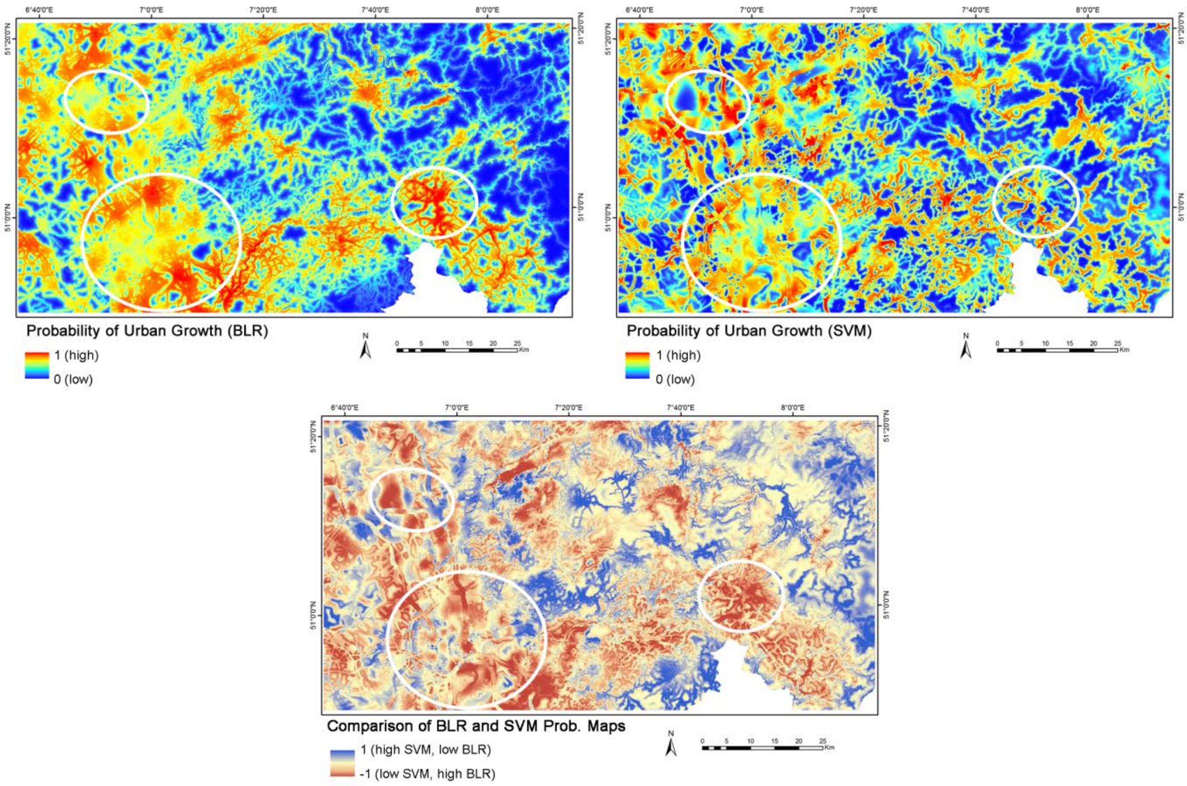

Figure 2.6. Probability maps (top) of the BLR (left) and SVM (right) model and the comparison map (bottom).

Another difference is the transition of areas with high probabilities into areas with low probabilities. While the BLR map shows smooth, gradual transitions covering extensive areas around the agglomerations, the SVM map is characterized by strong, sharp edges. Having a look at the aggregated histograms of both maps give more insights regarding their behavior (Fig. 2.7). The BLR as well as the SVM histogram exhibit most of the values in lower percentiles, which indicates that both models spot a greater part of the non-urban growth pixels. The BLR reaches a probability maximum of 94% and the SVM one of 99%. Both models assign a steady amount of pixels to medium probabilities so that they incorporate a kind of uncertainty regarding the probability of urbanization (cf. 2.4.4). Here, the BLR histogram shows a steady increase of high probabilities and then a faster decrease in areas of higher urban growth probabilities. The same pattern is given in the SVM histogram, but one can observe distinct differences at probabilities around 10%, 35%, and 70% missing in the BLR histogram. Probabilities between 90-95% are not even present in the SVM map. Assuming a similar distribution as the SVM training data (Waske et al., 2010), this finding may reflect the specific separation procedure of SVM: constructing an optimal hyperplane based on few characteristic vectors (VAPNIK, 1995, 1998). However, in total, the SVM approach assigns more values in the edge regions of 0-33% (290,970) and 67-100% (122,631) than the BLR (288,088 and 108,979). In contrast, values in between have a lower amount (257,321) than the BLR approach (273,855). These values indicate a kind of indecision whether a cell is more likely to be urbanized or not. The topic of uncertainty is an important issue to be discussed in the validation section 2.4.4. Subsequently, the driving forces determining the characteristic patterns of the probability maps as wells their performances in the BLR and SVM model are discussed.

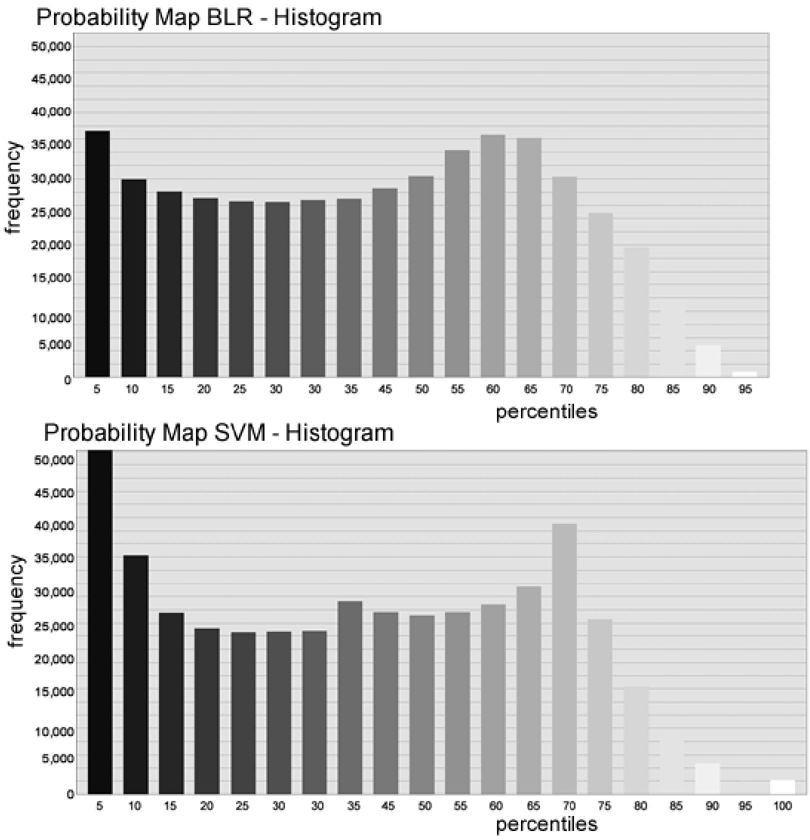

Figure 2.7. Histogram of the probability maps of the BLR (top) and SVM (bottom) model.

2.4.2 Driving Forces of Urban Growth

Reliable indicators for assessing the influence of the driving forces selected for the models are the rank of a variable within the feature selection (SVM) and the regression coefficients (BLR) shown in table 2.1. In contrast to linear regression models, the regression weights of a BLR model allow no insight into the direct effect on the dependent variable but on their logarithmized odds (LESSCHEN et al., 2005). However, the direction of the effect can be analyzed. Again, it has to be considered that the interpretation of the BLR regressors as well as the SVM feature selection focuses on analyzing the interaction of the variables in total, not their individual effect on urban growth (HSU et al., 2010; MENARD 2001).

It can be stated that every variable indicating the occurrence of settlements in the base year 1984 (e.g. distance variables, population density, jobs and unemployment rate) consequently has a negative influence on the probability of urban growth. The same goes for elevation and slope. Although slope is already included in the UGMr algorithm, we added it to the driving factors to amplify the performance of the BLR model. Variables increasing the probability of urban growth are the migration rates of persons at the age of 25 to 50 as well as the per capita net dwelling area.

With respect to comparability reasons, all variables were also used for the training of the SVM model. After several forward feature selections, six variables were eliminated. Hence, in terms of data "hungriness" (LEE, 1973: 165), the BLR model makes use of 17 variables, the SVM model only needs 11 for achieving its best performance. The first variable depicted in the selection was the distance variable "DistRiver". Together with "DistAirport" it indicates the Rhine agglomeration of Cologne and Düsseldorf exhibiting the highest absolute growing rates of settlement areas in the study region (MIELKE & MÜNTER, 2008). One should note that the occurrence of the Rhine stream was the main factor for the first roman settlements along this natural border of their empire (LAUX & ZEPP, 1998). They acted as a kind of growth nuclei and, of course, the Rhine itself served and serves as an international trade way. It became one of the most frequented waterways of the world and together with its tributaries it drove forward the urbanization in the region starting the era of industrialization (MAYR & TEMLITZ, 2006). Beside the other distance variables, the driving factor of the labor market ("JobsSec" and "JobsTert") and the living conditions ("NetDewllArea") achieve the best results in combination with the aforementioned variables.

Several studies about the influencing factors on urban growth in Germany show that land consumption cannot be explained by focusing exclusively on the demand (people) and the economy (jobs) (SIEDENTOP, 2006). Particularly migration patterns for the age group from 25 to 50 years have an influence on the intensity of land consumption (BMVBS/BBSR, 2009). Our results reflect this observation. Most demographic variables (e.g. population density) and economic variables (e.g. jobs) show a negative relation to urban growth: new settlements are developed predominantly in the suburban and rural regions of the study area and thus in areas with a relatively lower population and job density. At the same time there is a positive relation between the migration pattern for the age group 25 to 50 years and urban growth: new settlements are developed in regions where a positive migration rate of this age group can be observed. The approach is straightforward. A clear distinction between what may be cause and what effect needs to be further investigated (VERBURG & VELDKAMP, 2005). Admittedly, by using dasymetric mapping for the creation of spatially explicit "location specific characteristics" (VERBURG et al., 2004a: 146), the risk of incorrect cross-level deductions in terms of ecological fallacy is reduced but it is not yet totally eliminated (ROBINSON 1950).

2.4.3 Calibrating the Cellular Automata

The BLR and SVM probability maps based on various driving forces of urban growth are combined with the exclusion layer of UGMr. In total, three different versions of UGMr are constructed:

- UGMr-AR: Exclusion layer (areas where urban growth is restricted such as water bodies, natural reserves etc.).
- UGMr-BLR: Exclusion layer and probabilities for urban growth based on the BLR analysis.
- UGMr-SVM: Exclusion layer and probabilities for urban growth based on the SVM analysis.

Table 2.2 shows the resulting growth coefficients and MRV values of the calibration process for all three models. The calibration performance is very good with a mean factor of agreement over all resolutions (F_t) around 0.97. High urbanization rates are represented by high growth coefficient values (CLARKE et al. 1997, GOETZKE 2012). The observed urban growth in the study area for the time span 1984-2001 is relatively low. Thus, the growth coefficients are accordingly lower than compared to recent studies using SLEUTH (RAFIEE et al., 2009; SILVA & CLARKE, 2005; WU et al., 2008).

Table 2.2. Growth coefficients and MRV mean factor of agreement over all resolutions (F_t) of the calibrated UGMr models (1984-2001).

	UGMr-AR	UGMr-BLR	UGMr-SVM
Slope	6	20	18
Dispersion	5	5	9
Breed	9	11	19
Spread	5	9	9
Road	70	80	90
F_t	*0.978*	*0.978*	*0.979*

Additionally, the growth coefficients are an indicator for the amount of possible urban cells selected during a growth cycle (CLARKE et al. 1997; SILVA & CLARKE, 2005). Higher coefficients mean that more urban cells need to be tested for their suitability before allocated in the particular growth simulation. If UGMr is run without a probability map or an exclusion layer, nearly every cell has the same probability of urbanization. The growth coefficient is quite low. In contrast, probability maps might increase the possibility that a particular cell is not suitable for being urbanized. In order to reach the estimated growth rate, more cells have to be depicted and tested to find out whether they are suitable or not. The growth coefficient increases. The enhanced versions of UGMr show higher spread values than UGMr-AR. More cells during a growth cycle are tested for urbanization in terms of edge growth.

A high slope coefficient means that already slight slopes reduce the probability to allocate urban cells. Thus, the comparatively high slope coefficients of the integrated versions of UGMr occur due to the fact that both probability maps assigned low probabilities to the hilly areas of the Bergische Land.

The differences regarding the dispersion and breed coefficients are very interesting. Here, UGMr-BLR and UGMr-AR are showing significantly lower growth values than UGMr-SVM.

The dispersion and breed coefficients regulate the diffusive, scattered type of growth observed especially in the rural hinterland of the large agglomerations. Here, UGMr-AR and UGMr-BLR exhibit low values while UGMr-SVM detected possible areas of urbanization (cf. 2.4.1).

2.4.4 Validating the Cellular Automata

Unlike the procedure in the calibration process, we removed all persistent urban areas between 1975 and 2005 for validating the model results. Thus, we can exclusively assess the ability of the model to simulate urban growth over three decades of urban expansion in NRW. The era includes processes of suburbanization and urban sprawl of the agglomerations at the Rhine River, urbanization of the rural east of the study area, and a cautious re-concentration of population and jobs in the core cities (LAG 21, 2008).

The validation of complex system models such as CA not only includes careful error estimation but also addresses the uncertainty of the model results (MESSINA et al., 2008). UNWIN (1995: 551) defines uncertainty in terms of spatial simulations "as a measure of doubt and distrust in results" which can be seen as a certain kind of vagueness due to stochastic variability (WEGENER, 2011). For assessing the uncertainty of CA like UGMr, a closer look at the outcomes after 100 MC is a proved procedure (AERTS et al., 2003). Table 2.3 shows the allocated new urban cells in three percentile groups. At first glance, the three models show a stochastic noise in the urban growth pattern; a well-known problem of SLEUTH (CHAUDHURI & CLARKE, 2013) and of UGMr respectively. The distribution shows that a low cut-off value will decrease the reliability of the model outcomes. The integrated versions of UGMr exhibit a higher certainty in their performance than UGMr-AR as more pixels are chosen more frequently and a higher maximum allocation value is achieved.

Table 2.3. Percentiles of times a pixel is chosen as a new urban cell (1975-2005; 100 MC).

Times a pixel is chosen	UGMr-AR	UGMr-BLR	UGMr-SVM
1-33	563,871	559,212	559,383
34-66	25,520	25,524	26,113
≥67	2,889	7,544	6,784
maximum value	88 times	96 times	97 times

For transforming the MC maps into a binary urban growth map, we have chosen a certainty of 33%. Here, the best balance between location and quantification performance could be reached. The total amount of urbanized area in our research transect between 1975 and 2005 is 50,967 ha. UGMr-SVM (32,897 ha) and UGMr-BLR (33,068 ha) clearly exceed UGMr-AR (28,409 ha) regarding the simulated quantity of urban growth.

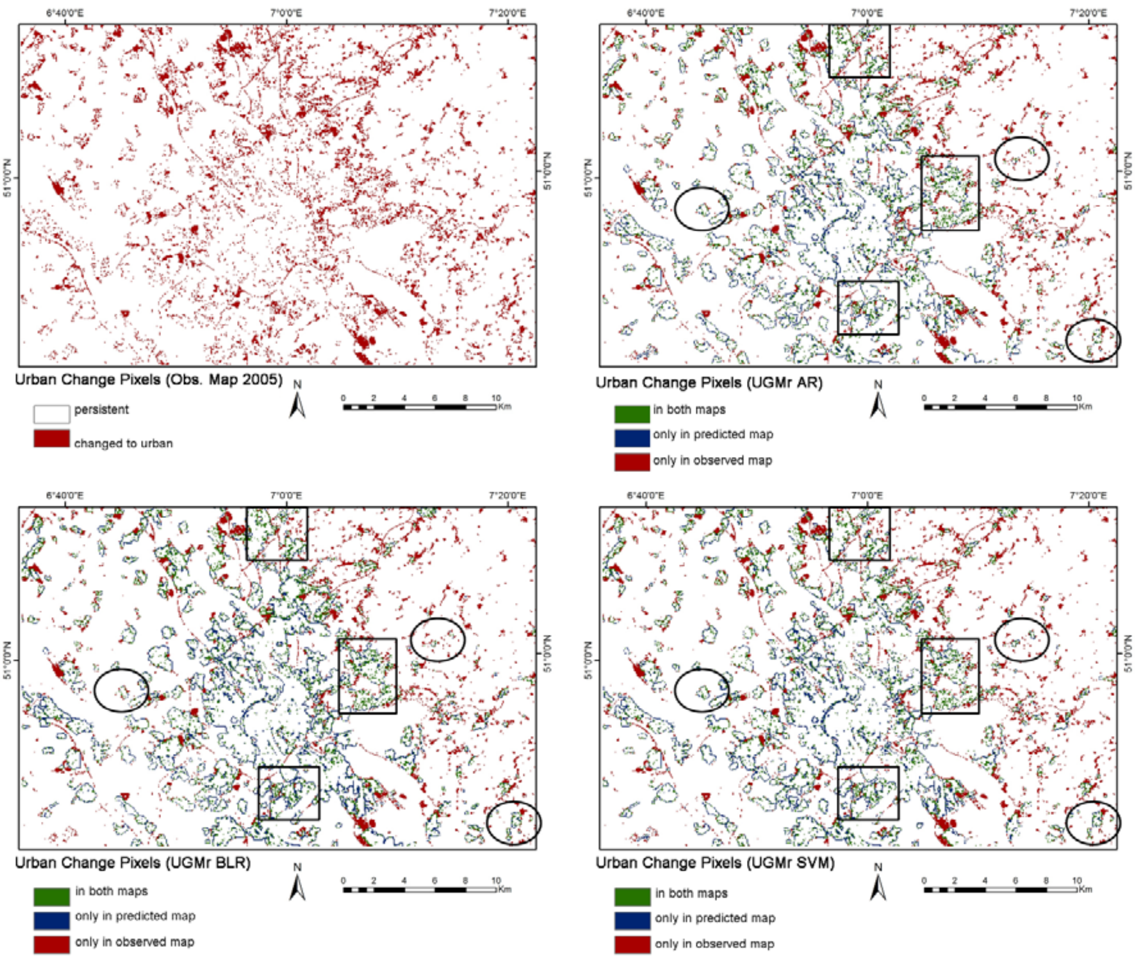

Figure 2.8. Observed urban growth in the area of Cologne 1975-2005 in comparison to the agreement results of UGMr-AR, UGMr-BLR, and UGMr-SVM (clock-wise).

Figure 2.8 shows the observed urban growth between 1975 and 2005 and the results of the comparison between the maps of the predicted and the observed urban growth of the three models. The maps show a pixel-by-pixel comparison between the predictions of the three UGMr variations and the observed validation data of the Cologne agglomeration area in 2005. It is one main drawback of spatially explicit land-use models in general and urban cellular automata in particular that greenfield development implemented by local planning is very hard to simulate. The sudden emergence of larger homogeneous areas can only be simulated if land development plans are provided and integrated in the model. Thus, no version of UGMr can simulate the growth of the autobahn A4, the expansion of the Cologne-Bonn airport, or the emergence of large shopping malls on greenfields. In this context, the advantage of UGMr is its application of spontaneous growth – e.g. as it is the case of the scattered pattern in the hilly regions of the Bergische Land – in combination with new spreading centers. Hence, some urbanized areas are captured more than confidently (Fig. 2.8, circles). Here, UGMr-BLR and UGMr-SVM can regulate the appearance of apparently random cells indeed. As supposed during the calibration phases while looking at the spread coefficients, both integrated UGMr versions allocate a higher quantity of extensive urban edge growth than UGMr-AR (Fig. 2.8, squares).

Again, it has to be stated that UGMr is a purely growth-oriented model. The CA exclusively models the transformation from non-urban cell states to urban ones. Yet, there is no chance of allocating urban shrinkage in terms of demolition or removal of sealed surfaces in a spatially explicit fashion. However, regional planning will need to deal with the phenomenon of extensive demolition – known as urban perforation – in the next years. For the given study period spatial urban growth still simultaneously occurs to a shrinking population (BBSR, 2012; SIEDENTOP, S. & FINA, S., 2008).

Table 2.4. Results of the accuracy assessment for UGMr-AR, UGMr-BLR and UGMr-SVM (1975-2005).

	AUC (after 100 MC)	**Kappa**	$\varkappa_{loc}$	$\varkappa_{histo}$	F_t
UGMr-AR	0.79	0.39	0.57	0.69	0.946
UGMr-BLR	0.80	0.42	0.55	0.77	0.948
UGMr-SVM	0.82	0.43	0.56	0.77	0.949

The validation results of UGMr-AR, UGMr-BLR, and UGMr-SVM are listed in table 2.4. The discrepancy between the overall agreement factors and the Kappa values is obvious. It is specific to land-use change models to underestimate the quantity of change and to miss the exact position of changes (PONTIUS, 2000; PONTIUS et al., 2008; PONTIUS & MALIZIA, 2004; VISSER, 2004). This difficulty is compounded by the fact that we have been focusing on urban growth since 1975 while discarding persistent urban cells. Thus, the ability to predict non-urban growth is not covered by the Kappa coefficient. The models' performances improve if we differentiate between location and quantification errors. In this case, the predictive efficiency of location is moderate ($\varkappa_{loc}$) and that of quantification ($\varkappa_{histo}$) is on a very good level. This index shows a clear increase of the quantity prediction by using the integrated versions of UGMr. As one can see from the Kappa results in general, the integrated versions of UGMr, and especially UGMr-SVM, are lifting the overall prediction accuracy in comparison to a random distribution from a poor to a fair level. A fair Kappa value does not mean that the model is far from being feasible for the application of real world scenarios. It only means that the constructed model is not feasible for the specific circumstances. Here, this would be a perfect local prediction with a spatial resolution of 100 m. Nevertheless, if spatially explicit land-use change models are allowed a certain tolerance range regarding the predictive efficiency of location, their accuracy will increase rapidly (PONTIUS et al. 2004; PONTIUS & MALIZIA, 2004).

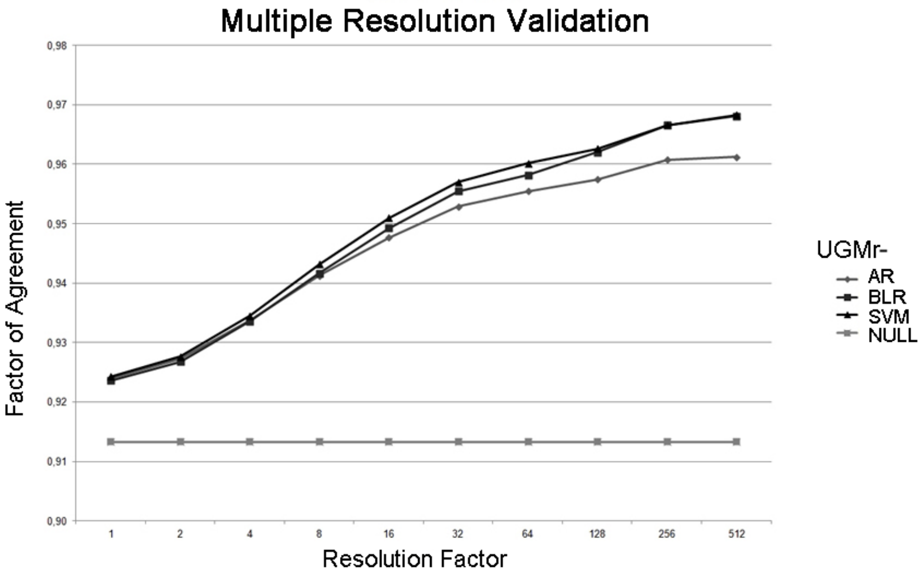

Figure 2.9. MRV Curves of UGMr-AR, UGMr-BLR, UGMr-SVM, and a null model.

The MRV results show an overall accuracy on an excellent level of agreement, which can be attributed to the ability of all three models to predict the location and the quantity of non-urban growth cell states almost perfectly. Likewise, they exceed the level of the null model already at resolution level one (Fig. 2.9). The agreement curve of the null model forms a straight line and reflects the low signal of urban growth in comparison to the very high signal of persistent non-urban growth cells. Again, the integrated versions of UGMr show a higher agreement between the predicted and the observed urban growth than UGMr-AR. While the F_t value has only slight differences between the three models, the curve of agreement over different resolution mirrors that the ones of UGMr-AR are saturated much earlier than the curves of UGMr-BLR and SVM. Obviously, UGMr-SVM has a steeper slope reflecting a more robust performance than UGMr-BLR.

The ROC tests the model in different scenarios of quantity of urban growth. Here, the integrated variations of UGMr achieved an enhancement of the prediction efficiency of one (UGMr-BLR) resp. two (UGMr-SVM) percentage points in comparison to UGMr-AR.

2.5 Conclusions and Outlook

It was the aim of this study to enhance SLEUTH by using SVM and to assess its performance in comparison with a BLR-based model. This is the first study linking the urban CA SLEUTH with the machine learning approach of SVM. We have assessed the accuracy of the spatially explicit urban growth models regarding their certainty (cut-off value) and their probability performance (ROC) in comparison with the randomness (Cohen's Kappa), the quantity ($\varkappa_{\text{histo}}$) and the allocation ability of urban growth ($\varkappa_{\text{loc}}$) as well as the fuzziness and the overestimation of urban growth (MRV). The calibration and the validation of the model have been separated carefully. As a reliable result, it can be stated that the quantity and allocation performance of SLEUTH UGMr are augmented clearly when coupling it with a BLR- or SVM-based probability map. The combination enables the dynamical simulation of different growth types on the one hand as well as the analyses of various geophysical and socio-economic forces driving the local suitability of urbanization on the other hand.

A feature selection has been carried out and the effect rank of the variables in the SVM model has been analyzed. The SVM approach has needed less input features than the BLR model. The effect direction of the included driving forces is only understandable when linked to the BLR model. Urban growth takes place predominantly in areas with a relatively lower population and job density. A positive relation between the migration pattern for the age group 25 to 50 years and urban growth could be revealed. A clear separation of cause and effect remains an objective for future research.

It has been shown that SVM are not only useful for solving classification problems in remote sensing but also for a diversified and robust creation of probability maps in the context of land-use modeling. SVM-based probabilities exhibit a higher certainty compared to those derived by BLR. Interestingly, this certainty could not be transferred directly into UGMr. UGMr-BLR performs nearly as certain as UGMr-SVM. Though distinctly more certain than the "unguided" UGMr, the stochastic variability is still very high. A careful cut-off value selection is highly recommended. Finally, the allocation ability as well as the probability performance of UGMRr-SVM slightly exceeds the one of UGMr-BLR.

As a next step, coupling different modeling techniques for prediction and process analyses of urban land-use and land-cover change should be pushed beyond the physical restriction of pixels. To incorporate the irrational human component impacting on all spatial and temporal levels between the household and the global scale, pixels must be coupled with people. This can, for instance, be done by extending the enhanced version of UGMr with a multi-agent system. That way, one can study emergence phenomena resulting from complex behavioral interaction processes on the micro scale. Hence, the simulation of urban change could be extended from analyzing growth processes to the estimation of urban decline. Coupling actors with factors would be a chance to overcome formal equations. Therefore, the present ride on the surface of an ocean of driving forces, pressures, states, impacts, and responses would be changed into diving right into it.

3 Geosimulation of Urban Growth and Demographic Decline in the Ruhr: a Case Case Study for 2025 Using the Artificial Intelligence of Cells and Agents

Source: RIENOW, A. & STENGER, D. (2014): Geosimulation of Urban Growth and Demographic Decline in the Ruhr: a Case Case Study for 2025 using the Artificial Intelligence of Cells and Agents. Journal of Geographical Systems, 16(3), 311-342.

Abstract

The Ruhr is an "old acquaintance" in the discourse of urban decline in old industrialized cities. The agglomeration has to struggle with archetypical problems of former mono-functional manufacturing cities. Surprisingly, the image of a shrinking city has to be refuted if you shift the focus from socio-economic wealth to its morphological extension. Thus, it is the objective of this study to meet the challenge of modeling urban sprawl and demographic decline by combining two artificial intelligent solutions: The popular urban cellular automaton SLEUTH simulates urban growth using four simple but effective growth rules. In order to improve its performance, SLEUTH has been modified among others by combining it with a robust probability map based on support vector machines. Additionally, a complex multi-agent system is developed to simulate residential mobility in a shrinking city agglomeration: ReHoSh (Residential Mobility and the Housing Market of Shrinking City Systems) focuses on the dynamic of interregional housing markets implying the development of potential dwelling areas. The multi-agent system comprises the simulation of population patterns, housing prices and housing demand in shrinking city agglomerations. Both models are calibrated and validated regarding their localization and quantification performance. Subsequently, the urban landscape configuration and composition of the Ruhr 2025 are simulated. A simple spatial join is used to combine the results serving as valuable inputs for future regional planning in the context of multifarious demographic change and preceding urban growth.

3.1 Introduction

It is safe to say that the Ruhr is an icon in the discourse of urban decline and structural transformations in old industrialized cities. Like other members of the "rusty belt", the Ruhr has to struggle with archetypical problems of former mono-functional manufacturing cities depending on mining and heavy engineering. Paradoxically, the image of a conurbation on the pathway of urban decline has to be refuted if you shift the focus from societal change and economic wealth to its morphological extension. Like in most parts of Central Europe, urban sprawl as an urbanization process spilling over the actual urban agglomeration borders and creating a spatial footprint of impervious surface has been one of the most striking land-use change processes in the Ruhr. The quantitative and qualitative measurement, prospection, and evaluation of patterns and processes of urban systems are all part of land-systems science. Urban system models have to handle complexity in terms of spatiotemporal dynamics, self-organization, adaptivity, and dynamical reciprocity between several organizational levels (ALCAMO et al., 2006; BATTY, 2005; BENENSON & TORRENS, 2004). Processes occurring at the micro-scale determine patterns of the macro-scale and one can surely go one step beyond Aristotle's phrase "the whole is more than the sum of the parts" in characterizing urban systems by the statement "the whole . . . [is]… not only more but very different from the sum of the parts" (ANDERSON, 1972: 393). Currently, a new generation of land-use models is emerging leaving the bases of general system theory to meet the challenge of simulating complex urban systems (ALCAMO et al., 2006; BATTY, 2005; VERBURG, 2006a). In this context, artificial intelligence (AI) moves beyond static statistical techniques and benefits from the great strides of computational progress to provide a deeper insight into causes and effects of urbanization (BATTY, 2005; BENENSON & TORRENS, 2004; BETHELL, 2006; WU & SILVA, 2010; SILVA & WU, 2012).

Among those AI techniques are cellular automata (CA) and multi-agent systems (MAS). While CA focus on discrete spatial entities, MAS are well-suited to capture autonomous individual decision making. CA are defined by cell states as well as transition rules, MAS often work spatially implicit as a community of agents rather related to each other through communication and actions than through fixed spatial links (ALBERTI & WADDELL, 2000; KOCH, 2003). Linking pixels and people is one of the leading challenges in land-systems science (GEOGHEGAN et al., 1998; LESSCHEN et al., 2005; RINDFUSS & STERN, 1998; WOOD & SKOLE, 1998). LAUF et al. (2012a) and HAASE et al. (2012) present two approaches applied to the simulation of physical and demographic urban development in cities simultaneously dealing with growth and shrinkage (Berlin, Leipzig). Both studies use a CA for spatially explicit urban land-use modeling. In order to guide its allocation ability and to set the necessary demand, a system dynamic model (SD) focusing on household preferences is used. Additionally, possibilities for a future integration of MAS are examined (HAASE et al., 2012). This paper tries to broaden the research activities of future urban development in declining regions. We present a loose coupling approach addressing the morphological urban growth influenced by location-specific characteristics as well as the dynamic interdependencies of interregional housing markets. Instead of focusing on one city (HAASE et al., 2012; LAUF et al., 2012a), we apply the approach to the polycentric region of the Ruhr consisting of 15 cities and districts. The popular urban CA SLEUTH is used to simulate the region's urban growth for 2025. As a bottom-up approach the model can easily be transferred to other regions (CHAUDHURI & CLARKE, 2013; SILVA & CLARKE, 2005; GEOGHEGAN et al., 1998). SLEUTH calculates urbanization rates by analyzing past urban patterns to fit its growth coefficients during the calibration phase. For enhancing its modeling performance, we use the machine learning algorithm of support vector machines (SVM) to incorporate macro-scale driving forces affecting the local suitability of urban land use (LESSCHEN et al., 2005; VERBURG et al., 2002, 2004b). We waive an SD application for two reasons. Firstly, SVM are appropriate in terms of land-cover classification exhibiting high accuracies and deliver a kind of variable hierarchy through a specific feature selection (HSU et al., 2010; WASKE et al., 2010). Secondly, SD models are highly elaborated to establish socioeconomic relationships but lack dynamic adaptations on changing system states (VERBURG 2006a, LOIBL & PETERS-ANDERS, 2003; SCHOLL, 2003; HAASE et al., 2012; LAUF et al., 2012a). Instead, a complex agent-based city model is developed to fill this gap and simulate residential mobility driven by individual decision making as well as interactive reactions of the supply side. ReHoSh (Residential Mobility and the Housing Market of Shrinking City Systems) comprises not only household preferences (HAASE et al., 2012; LAUF et al., 2012a) but also the development of potential dwelling areas as well as housing prices and housing supply. SLEUTH-SVM and ReHoSh are run separately while the results of both AI models will be brought together for an integrated spatial analysis. The main input data of SLEUTH are land-cover maps with discrete urban classes. In contrast, ReHoSh is set-up with aggregated zonal statistics and household characteristics. Thus, we are dealing with a multiple scale analysis crossing individual, communal, and regional scales. In a nutshell, the study focuses on the following research objectives:

1. The spatially explicit modeling of urban growth in the Ruhr for 2025 by using SLEUTH-SVM as suitability-guided CA.
2. The simulation of intraregional population migration and housing price changes in the Ruhr for 2025 formalized as agent interactions in ReHoSh.
3. The loose coupling of both AI results for analyzing the development of different household types and housing prices in terms of their spatial distribution.

Figure 3.1 visualizes the simulation framework of the study.

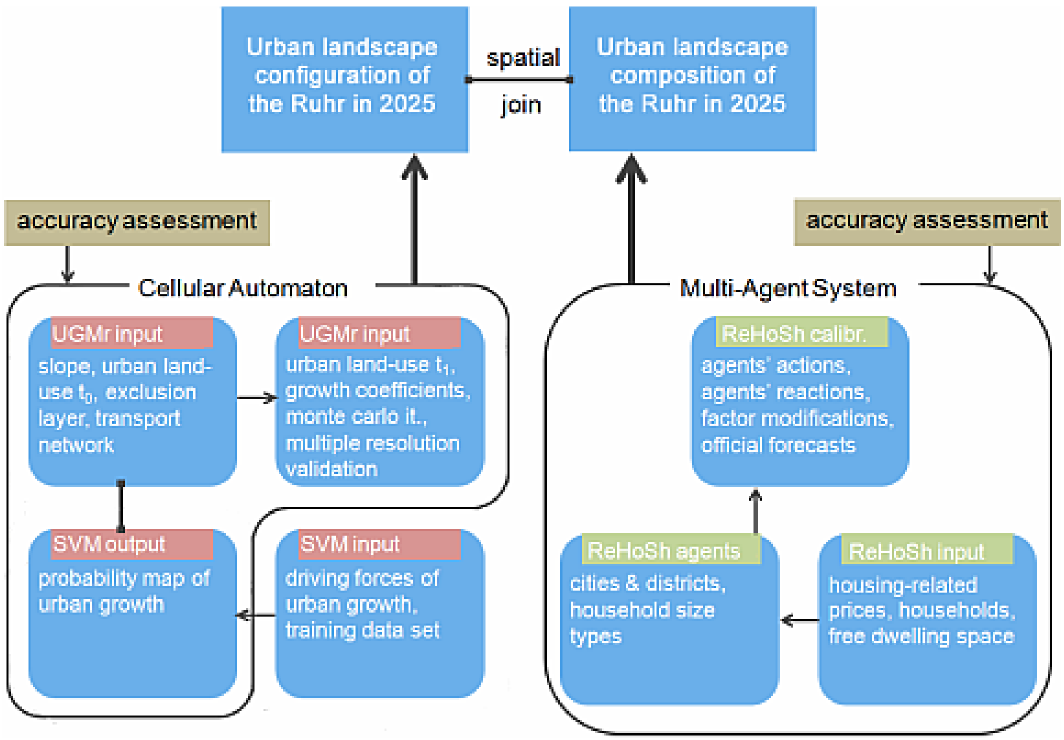

Figure 3.1. Workflow including the data and methods used in this study.

The paper is structured as follows: Section 3.2 introduces the research area. The subsequent sections discuss the calibration, validation, and implementation of SLEUTH-SVM (Sect. 3.3) and ReHoSh (Sect. 3.4). Section 3.5 presents the spatially explicit and implicit results of the urban landscape configuration and composition of the Ruhr in the year 2025. The advantages and limitations of linking pixels and people in urban system modeling as well as the issue of calibration and validation challenges in multi-scale and multi-model geosimulation will be discussed critically. Finally, section 3.6 provides a short conclusion and gives an outlook for future research.

3.2 The Ruhr – A Shrinking Metropolis?

3.2.1 Urban Decline

The study area lies in North Rhine-Westphalia (NRW) in the western part of Germany (Fig. 3.2). It extends from the Lower Rhine basin in the west to the Westphalian Plane in the north and the Rhenish Massif in the south. With its polycentric and administratively fragmented structure but homogenous and extensive urban area the Ruhr is a worldwide unique urban entity. In general, 11 cities and 4 districts form the biggest agglomeration (1,150 people p. km^2) in Germany, and with its 443,969 ha it is the fifth largest urban region in Europe. The biggest cities of the Ruhr are – in descending order – Dortmund, Essen, Duisburg and Bochum; each with a population of 370,000 to 580,000.

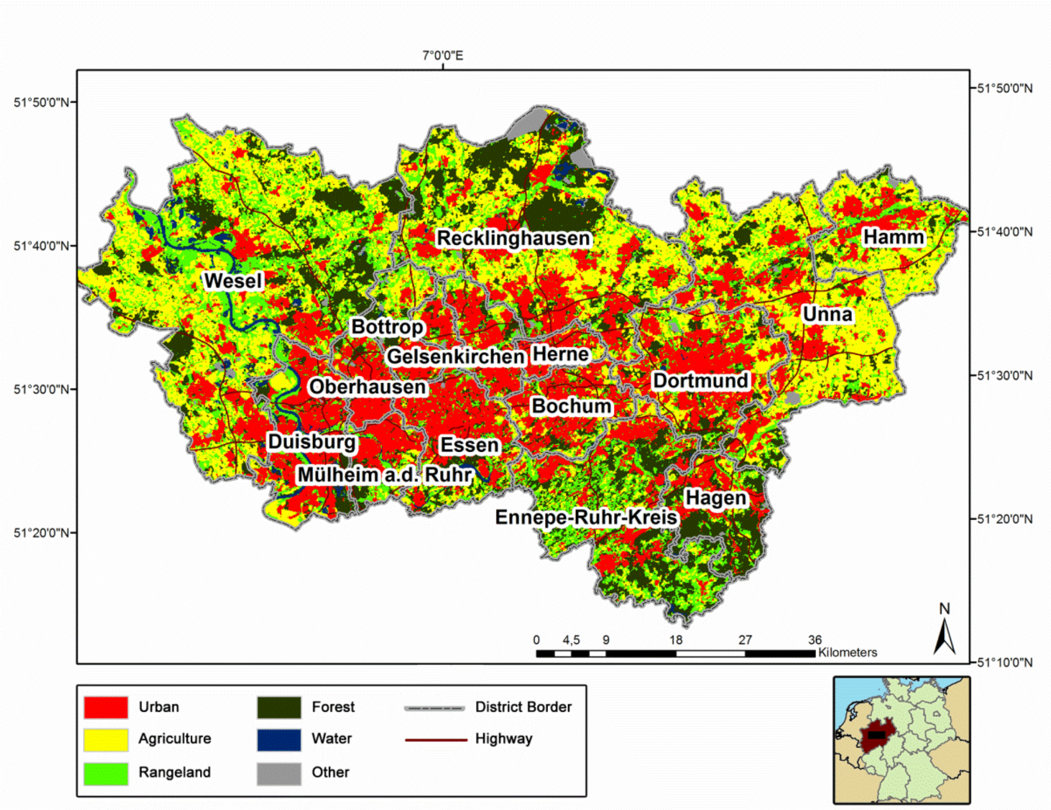

Figure 3.2. Land-use map with cities and districts of the Ruhr (North Rhine-Westphalia).

The basis for the rapid economic, demographic, and morphogenetic growth of the Ruhr at the turn of the 20th century was built during the age of industrial mining, the spread of ironworks, the railway expansion, and the foundation of the Zollverein in the middle of the 19th century. The era of prosperity lasted until after the war. The cultural identity of the people in the Ruhr is closely intertwined with the industrial heritage. This is reflected in the way that elements of the natural landscape had been utilized. Thus, the tectonic faults delivered the carbon and ore that were refined in the steel works, and the rural hinterland provided agricultural products. The three rivers crossing the Ruhr from the mountainous east to the western Rhine valley also obtained different social functions: The Ruhr (river) as a potable water reservoir, the Lippe as a cooling water pool, and the Emscher as a famous wastewater drainage. The Rhine itself served and still serves as an international trade way so that the harbor of Duisburg became the world's largest inland port. Today, numerous renaturation sanctions, university buildings, and urban entertainment centers turn the image of the Ruhr as a sealed moloch with nights aflamed by smelting furnaces and freshly washed clothes colored black by smut into a cliché. Only the fine-meshed net of autobahns, museum constructions, and, above all, the multicultural population give evidence of the region's industrial past.

Many studies analyze the Ruhr in the context of urban decline and structural transformations of old industrialized cities (COUCH et al., 2005). Like other mono-functional manufacturing cities the Ruhr faces a demographic decline, an aging population, high unemployment rates, brain drain and a lack of incentives to attract prosperous companies of the service sector, especially the "new economy" (BLOTEVOGEL, 2006; COUCH et al., 2005; DANIELZYK, 2006; GRÜBER-TÖPFER et al., 2008). A first glance at the key indices confirms this impression: the overall population decreased from 5.4 to 5.1 M between 1996 and 2010, one in ten persons is unemployed and the amount of employees working in the service sector stagnated at 72 % for twelve years. Accordingly, the Ruhr has been characterized demographically as a stagnating old center of employment (BROWN et al., 2004; BLOTEVOGEL, 2006; DANIELZYK, 2006; GRÜBER-TÖPFER et al., 2008). In addition, the Ruhr has been showing shrinking tendencies caused by a birth deficit, which interferes with population increases that may arise due to migration. Shedding light on the socioeconomic trends of the whole European Metropolitan Region Rhine-Ruhr, you can consequently attest a bipolar development: the south (Cologne, Düsseldorf, and Bonn) with an account in balance and the north (Ruhr agglomeration) with an account showing a debit (KNAPP, 1997).

3.2.2 Urban Sprawl

The increase of developed area and traffic contrasts with the stagnation and decrease of population and job numbers in the Ruhr region. Land consumption is a ubiquitous process in Germany. While rural regions show the highest relative increases in urbanization, the already urbanized regions show the highest absolute increases – despite population decreases or economic recessions (HIRSCHLE & SCHÜRT, 2008; SIEDENTOP & KAUSCH, 2004). This creates a zero-sum game of decreasing demand and abandoned property on the one hand and changing quality standards and location on the other hand (COUCH et al., 2005). There are several causes counteracting the demographic decline: the pluralism of lifestyles, the increasing demand of the housing space per capita, a car-oriented society, remaining effects due to an aging population, new leisure and purchase proposals as well as a competition of communities for industry or trade, and the steady wish for owning a home in greenfield areas. They occur parallel, synergistically or as a feedback loop of causes and effects to the extensive urban land-use change (LAMBIN & GEIST, 2006). Thus, land development is kept on a constant level (MIELKE & MÜNTER, 2008). Between 1975 and 2005, the agglomeration grew around 37,022 ha with a total urban area of 94,990 to 132,012. Its physiognomic pattern is dispersed and concentrated in the urban fringes, in the exurban areas as well as in small and middle towns in the cities' functional field of gravity (SIEDENTOP, 2006).

3.3 The Cells – Simulating Urban Sprawl

3.3.1 SLEUTH – An Urban Growth Model

Cellular Automata (CA) are one of the most popular simulation tools in geography. Their handling is simple and at the same time they are able to capture complex patterns of development (RUCKER, 1999; VON NEUMANN, 1951; ULAM, 1952). Urban growth simulation CA were developed by TOBLER (1975), WHITE & ENGELEN (1993), BATTY & XIE (1997), WU & YEH (1997), LANDIS (2001), and CLARKE et al. (1997). In CLARKE'S Urban Growth Model (UGM), more commonly known as SLEUTH, urbanization is seen as a diffusion process of complex urban patterns. It has been applied in urban growth studies all over the world (CHAUDHURI & CLARKE, 2013; CLARKE et al., 1997; RAFIEE et al., 2009; SILVA & CLARKE, 2005; WU et al., 2008). SLEUTH is an acronym of its initial input factors: slope, land use, exclusion, transport, and hillshade. Five growth coefficients (dispersion, breed, spread, slope, road gravity) define four growth rules: spontaneous growth, reflecting the random emergence of new urban areas, new spreading center growth, edge growth depicting urban sprawl, and road-influenced growth. The last one is UGM-specific and relocates a temporary cell along the road to its final position. Space and time are treated discretely in the CA. One growth cycle represents one year of urban growth and consists of the four aforementioned subsequent growth rules. Each selected new urban cell is compared to the local slope and exclusion information as well as a random value. The growth coefficients are defined during the calibration process of UGM. Every parameter combination of the particular growth coefficients between values of 0 to 100 is tested until the optimal balance is assessed. In his thesis, GOETZKE (2012) modified UGM and implemented it into XULU (eXtendable Unified Land use Modeling Platform), a modeling environment developed at the University of Bonn (SCHMITZ et al., 2005). The standard calibration evaluation method has been replaced by the multiple resolution validation (MRV) (PONTIUS et al., 2008). Thus, the urban land-use input is reduced from five to two. The modified version of UGM is referred to as UGMr (Urban Growth Model reduced). GOETZKE (2012) applied UGMr for a simulation run for the whole region of NRW and compared it with the original UGM defining the growth coefficients with Lee-Sallee index (DIETZEL & CLARKE, 2007). Besides showing that UGMr achieved a slightly higher accuracy than UGM, he was able to demonstrate that UGM achieves a better performance when using the same growth coefficients defined in the calibration run for UGMr (GOETZKE, 2012). To account for random variation built into the model, the result is a raster showing the frequency (over a predetermined number of Monte Carlo iterations (MC) that the model chose a cell to be urbanized. By using a cut-off value, the map can be transformed into a binary land-use map (GOETZKE 2012, RAFIEE et al., 2009; VERBURG, 2006a; WU et al., 2008).

The database consists of the mandatory slope and transportation layer as well as the urban land-use configuration. In this study, we define a cell as "urban" if it exhibits a high (≥ 33%) degree of imperviousness. Land-use data were retrieved from a time series of LANDSAT data. Time slices of the years 1975, 1984, 2001, and 2005 were classified by using a mixed approach of supervised classification algorithms and knowledge-based decision trees. Due to a post-classification correction, an accuracy of >85 % could be achieved. The detailed classification process is presented by GOETZKE et al. (2006) and SCHOETTKER (2003). These land-cover maps were reduced thematically to binary maps with classes "urban" and "non-urban". Due to computational reasons, we use a spatial resolution of 100 m (BARNSLEY et al., 2003; HOSTERT, 2007; RINDFUSS et al., 2008; SCHNEIDER, 2007; VERBURG, 2006a). The exclusion layer is optional for UGMr but we recommend it as it prevents the location of urban cells in, for instance, conservation areas or water bodies. Additionally, the exclusion layer can be combined with a probability map which enhances the performance (CHAUDHURI & CLARKE, 2013) and guides UGMr (BRIASSOULIS, 2000; LESSCHEN et al., 2005; PONTIUS et al., 2008; VERBURG et al., 2002).

3.3.2 Supporting UGMr with SVM – Pixels, People, Probabilities

RIENOW & GOETZKE (2014) have shown that SVM are able to guide UGMr and to augment its spatial allocation performance. SVM are well-established in land-use classification challenges showing very high accuracies (DRUCKER et al., 1999; GUO et al., 2005; MOUNTRAKIS et al., 2011; WASKE et al., 2010). Moreover, they are finding their way into land-use modeling applications (HUANG et al., 2010; OKWUASHI et al., 2009; XIE, 2006; YANG et al., 2008). CORTES & VAPNIK (1995) were the first to outline and present them in their simplest form as a linear binary classifier. They label empirical data by constructing an optimal separating hyperplane defined by characteristic vector values: the support vectors. The main advantage of SVM is the option to transform the model in order to solve non-linear classification problems. The mathematical background of structural risk minimization, large margin classification, and optimization problems is explained by VAPNIK (1995, 1998) and BURGES (1998).

In this study, SVM are applied to raster layer stack consisting of different geophysical, socioeconomic as well as demographic driving factors of urban growth. The selection is based on recent empirical studies dealing with urban sprawl in Central Europe (ANTROP, 2004; MIELKE & MÜNTER, 2008; SIEDENTOP, 2006; VERBURG et al., 2004a). For the construction of the SVM model we adapted imageSVM® of the EnMAP Toolbox® developed at the Humboldt University of Berlin. This software offers the possibilities of selecting the most important features of the training data set and of eliminating redundant data (HUGHES, 1968; NGUYEN & de LA TORRE, 2010; MEWES, 2011). The forward feature selection (HSU et al., 2010; WASKE et al., 2010) trains each of the input features. The best performing feature is selected. The remaining features are used for training but in combination with the initially selected one. The procedure is repeated until all features have been selected. The result is a ranking of the different features according to the corresponding agreement value. The features which start to weaken the SVM classifier can be eliminated.

Table 3.1. Variables⁺ selected for SVM model.

Name	**Description**	**Rank***
Distance-related variables		
DistAirport	Cost-weighted distance (CWD) to next international airport	5
DistCity	CWD to next city > 25.000 inh.	3
DistHighway	CWD to next highway exit	2
DistRailway	CWD to next railway station	1
DistRiver	Euclidian distance to next river	6
HighwayBuffer	500 m buffer to highways	n.i. X
Geophysical variables		
Elevation	Elevation above sea level (m)	11
Soil depth°	Vertical extent of soil layer (cm)	n.i.
Soil type°	Soil type defined by grain size (nominal)	n.i.
Soil quality°	Agricultural appropriateness (from [temporary] "not usable" to "very good agricultural location")	n.i.
Waterlogging°	Waterlogging type (from "low" to "very high")	n.i.
Water table	Depth of complete water saturation below ground (cm)	n.i.
Socioeconomic variables		
Income	Inverse distance-weighted (IDW) average income per month in district 1991	n.i.
Jobs	IDW number of jobs 1991	4
Land Price	IDW land value 1990	7
NetDwellArea	IDW per capita net dwelling area 1990	8
Unemployment	IDW unemployed per population 1991	9
Demographic variables		
Cars	Number of cars in district; Density Function (10 km kernel) DF	n.i.
Migration25-50	Difference between in- and out-migration per settlement of the group aged 25 to 50	n.i.
PopDens	Population density 1984; DF	10

⁺ Data sources are ATKIS (German federal topographic information system) and the State Office of Statistics.
*Rank according to the forward feature selection.
X Not included.
° Dummy coded.

It can be stated that the characteristic attributes of the distance-related variables (KOOMEN & BORSBOOM-VAN BEURDEN, 2011) and of the number of jobs are more suitable for constructing the SVM model than other socioeconomic or demographic variables. The distance to the next railway station in particular seems to be a very good indicator for a possible urbanization. This might be a link to the industrial past traversing the urban area by a freight transport network. Beside elevation – and slope, which already is a part of UGMr – no other geophysical variable is usable for the selection of areas suitable for urban growth with SVM. A further discussion of the included driving forces of urban growth is not included in this study since the goal is to generate a reliable probability map in order to enhance the performance of UGMr.

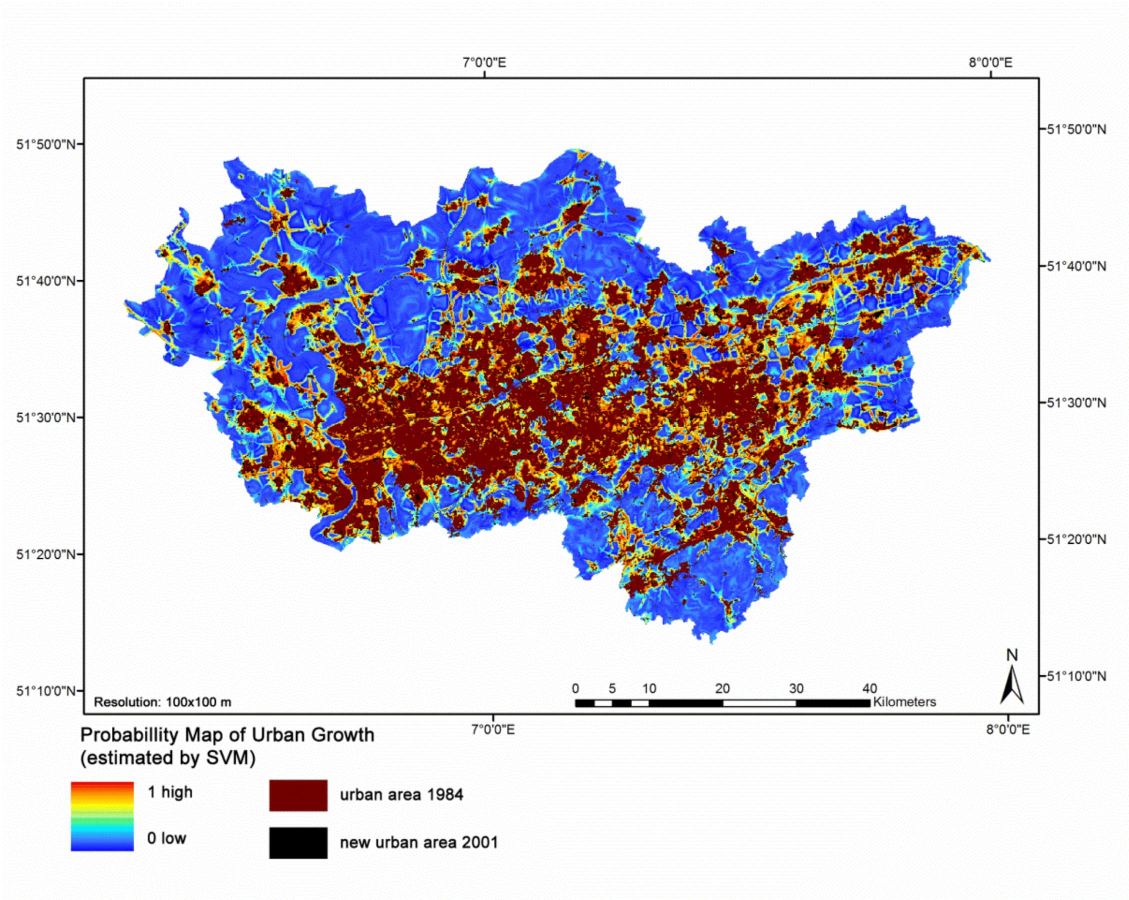

Figure 3.3. Probability map of urban growth derived from the SVM model and observed urban areas 1984 & 2001.

The output of the imageSVM® classification is not only a classified land-cover image but also an image containing the probabilities of each pixel for "urban growth" and "non-urban growth" (PLATT, 1999). The achieved SVM probability performance is very good and reaches an outstanding receiver operating characteristic (ROC) (PONTIUS & SCHNEIDER, 2001) of 0.94. Figure 3.3 shows the created probability map and the observed urban growth between 1984 and 2001.

3.3.3 Calibration and Validation of UGMr-SVM

Table 3.2 presents the growth coefficients of UGMr-SVM as well as the calibration (1984-2001) and validation indices (1975-2005). The calibration performance is very good with a mean factor of agreement over all resolutions (F_t) around 0.96. High urbanization rates are represented by high growth coefficient values (CLARKE et al., 1997; GOETZKE, 2012). The observed urban growth in the study area for the time span 1984-2001 is relatively low. In accordance, the growth coefficients are lower than those in recent studies (RAFIEE et al., 2009; SILVA & CLARKE, 2005; WU et al., 2008). The high slope coefficient means that already slight slopes reduce the probability to allocate urban cells. The cut-off value for transforming the map after 100 MC into a binary land-use map is chosen at 33%. At this level, the certainty of UGMr is reliable in terms of stochastic variability (CLARKE, 2004; WEGENER, 2011; UNWIN, 1995).

Table 3.2. Growth coefficients and validation results of UGMr-SVM, 1975-2005.

		UGMr-SVM
Growth Coefficients	Slope	90
	Dispersion	3
	Breed	4
	Spread	4
	Road	80
	Cut-off value	33%
Accuracy Assessment	$F_{t\ Calibration}$*	0.96
	$F_{t\ Validation}$	0.93
	ROC	0.79
	Kappa	0.80
	$\varkappa_{loc}$	0.93
	$\varkappa_{histo}$	0.87

* F_t is the mean factor of agreement over all resolutions of the MRV

The map comparison validated the model regarding its probability performance (ROC) in comparison with randomness (Cohen's Kappa), the quantity estimations of urban growth ($\varkappa_{histo}$), the allocation ability of urban growth ($\varkappa_{loc}$), and the fuzziness of urban growth (MRV) (LAUF et al., 2012a; MESSINA et al., 2008; PONTIUS et al., 2004; RUIZ et al., 2012; RYKIEL, 1996). The achieved results are on a very good level. Figure 3.4 contains the comparison map of the observed and the UGMr-SVM-predicted urban growth map for 2005. There are only few areas where UGMr acts "false-positively", meaning the model predicted urban growth where no growth has occurred (PONTIUS & SCHNEIDER, 2001). These are nearly always located in open-spaced inner city areas or clustered along recreational parks of the river Emscher between Bottrop and Essen. In contrast, there are more areas where the model simulates "false-negatively", which is predicting persistence where urban areas have spread in reality. Indeed, the urban areas in the district of Ennepe-Ruhr actually should have been captured. It seems that the slope coefficient of UGMr suppressed urbanization in this hilly region during the simulation run. However, in total, 108,220 ha of built-up land were predicted for 2005. This is a growth of nearly 14 % since 1975. In comparison, the observed urban growth rate is 39 %. The quantitative underestimation of the quantity of change is specific for spatially explicit land-use change models (PONTIUS, 2000; PONTIUS et al., 2008, 2004; VISSER, 2004).

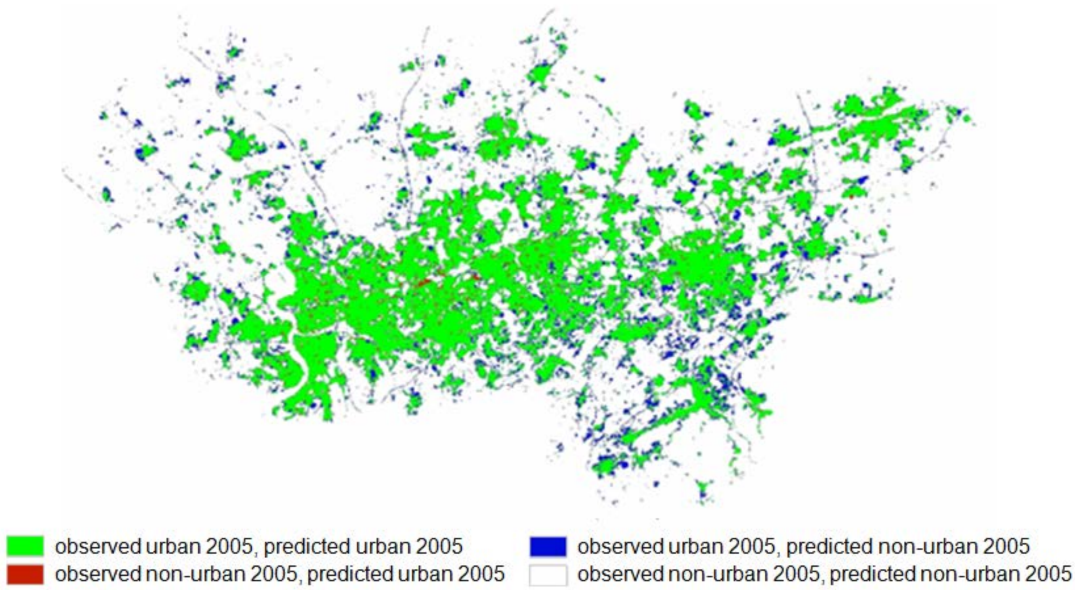

Figure 3.4. Agreement results of UGMr-SVM: comparison map of observed and predicted urban areas 2005.

UGMr-SVM is a purely urban growth model. The simulation of declining demographic processes in a morphogenetically growing region is neglected. For this, the results of UGMr-SVM must be pondered in the light of another AI solution: This is where the agents come into play.

3.4 The Agents – Simulating Demographic Decline with ReHoSh

3.4.1 Agents as Spatially Implicit Automata

The crucial point of MAS is the concept of agency. There are several definitions of agents and agency in terms of geosimulation (BENENSON & TORRENS, 2004; MANDL, 2003; NARA & TORRENS, 2005; STEVEN et al., 2002; SUDHIRA et al., 2005; VALBUENA et al., 2008; WU & SILVA, 2010). In this study, an agent is defined as an abstract entity (e.g. household or community) which is autonomous, intelligent, mobile, and adaptive. Here, an agent can be thought of as a kind of behavioral automata whose characteristic of proactivity is the most important quality distinguishing the MAS from the CA (LOIBL & TOETZER, 2003).

There are only a few studies dealing with the construction of an MAS in order to simulate urban processes in general and urban decline in Central Europe in particular. The micro-analytical model ILUMASS (BECKMANN et al. 2007; STRAUCH, 2003) developed for the analysis of land-use, transport and ecosystem relations by an interdisciplinary research association is the most elaborated but also the most complex model. It is very time-consuming and only implemented for Dortmund. This also holds true for the cost- and data-intensive MAS UrbanSim (WADDELL et al., 2008) tested for Zurich with limitations by LOCHL et al. (2007). The polycentric urban model of (LOIBL & TOETZER, 2003) focuses on housing decisions in growing suburban regions. An MAS dealing with the implications of urban shrinkage and demographic decline is RESMOBcity developed by HAASE et al. (2010). It simulates the population development on the spatial hierarchy level of neighborhoods based on a local household survey exclusively for Leipzig. In contrast, this study constructs an MAS which is suitable for the simulation of demographic decline in a polycentric urban agglomeration.

3.4.2 Theoretical Concept and Technical Implementation of ReHoSh

3.4.2.1 Assumptions

ReHoSh focuses on the dynamic of interregional housing markets implying the development of potential dwelling areas. The MAS comprises the simulation of population patterns, housing prices and housing demand in shrinking city agglomerations. The results of a model run are limited to influences of residential mobility, the reactions of the examined cities itself and the housing-related factors representing important issues of those regions (COUCH et al., 2005; HANNEMANN, 2002; SCHLEGELMILCH, 2009). All model dynamics and interactions are based on current theories and empirical studies in urban, population, and economic geography.

ReHoSh is based on six assumptions. Firstly, the thematic extent of all interactions being considered during a simulation run is limited to the housing-related factors. Other issues (e.g. diversification of lifestyles or business activities others than real estate) are excluded. Secondly, all households have unlimited knowledge of all possible dwelling places. This is important for the search for a new dwelling place as every household considers all cities within a certain distance without any restrictions. Thirdly, the prices for housing rise and fall linearly. Fourthly, cities expect an inelastic price behavior on the demand side. The latter two assumptions simplify the economic price system of ReHoSh. Fifthly, the housing supply at the beginning of the simulation is hard to calculate and is therefore assumed. Sixthly, the model simulates demographic change by a constant decrease of the Ruhr's total population. The change of household sizes, which results from demographic change (BUCHER & SCHLÖMER, 2003), is not considered. Any other possible exogenous impacts are not included in ReHoSh.

3.4.2.2 Agents, Interactions, Environment

The concept of ReHoSh can be divided into three key elements defined by MACAL & NORTH (2010) namely the agents itself, the interaction of the agents, and the environment.

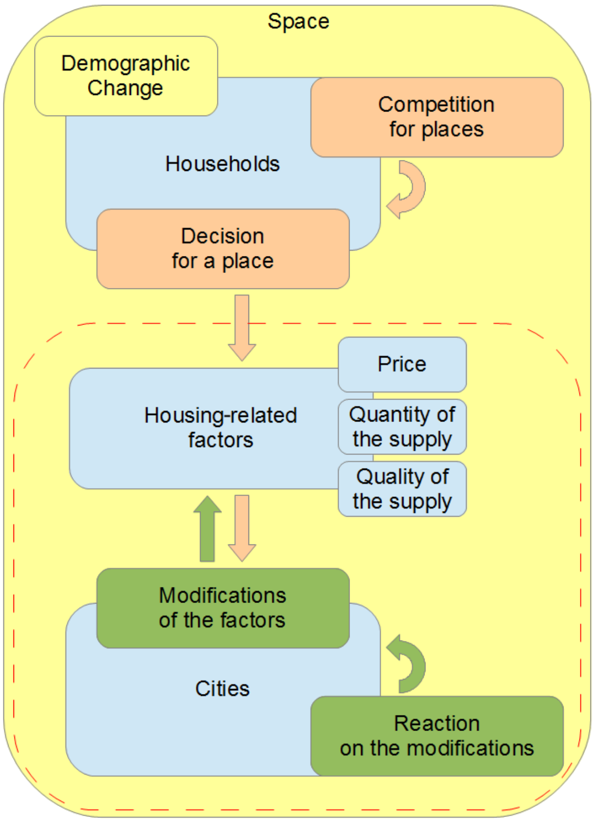

Figure 3.5. Main concept of ReHoSh showing the agents, the interactions, and the key factors of the MAS.

Figure 3.5 illustrates the main concept of the model. In the middle of the illustration the housing-related factors can be detected consisting of the price, the quantity, and the quality of housing supply. These factors are divided again into potential dwelling areas and properties. The households and the cities themselves represent the agents. Here, the cities aggregate not only administrative structures but also real-estate entrepreneurs and brokers. Both agents possess several attributes making them unique in their own group. Hence, several different household types can be considered and the cities can be distinguished by their housing-related factors. The households look for new dwelling places and compete with each other. The cities react to the decisions of the households and that of the other cities by modifying the housing-related factors. Those four interactions represent all possible actions being triggered during a simulation run. One simulation step of ReHoSh represents one year. The environment consists of the Ruhr's feature space, i.e. the global characteristics of the region like demographic change as well as the spatial positions of all interacting agents. While individual decision making is simulated on the residential scale the spatial resolution is scaled on one city or district as a whole. Thus, in contrast to UGMr-SVM, we deal with a spatially implicit approach. While in UGMr-SVM the research entities are 100 m cells depicting exact geographic localization information, in ReHoSh the positions of the households are associated with the coordinate of the center of the particular community.

3.4.2.3 From Intention to Action

A theory of human choice behavior is essential for an MAS dealing with residential mobility in urban systems (BENENSON & TORRENS, 2004; KOCH & MANDL, 2003). AJZEN (1985) formulated his theory of planned behavior and reasoned action, which implies a subsequent separation of behavioral intention from behavior limited by attitudinal influence. ReHoSh captures the idea of reasoned actions. Proactive household agents behave rationally but their way from the intention to move to the decision for a final destination is accompanied by several attitudinally bounded decisions in terms of location, housing type, and costs. The search of households for a new dwelling place consists of a three-step-pattern derived from migration theories and empirical urban studies: the intention to move, the search for a new place, and the actual decision for a new place (Fig. 3.6) as, for example, described by ROSSI (1980) or KALTER (1997). The decisions made during the search for a new place determine whether the households choose free spaces or properties.

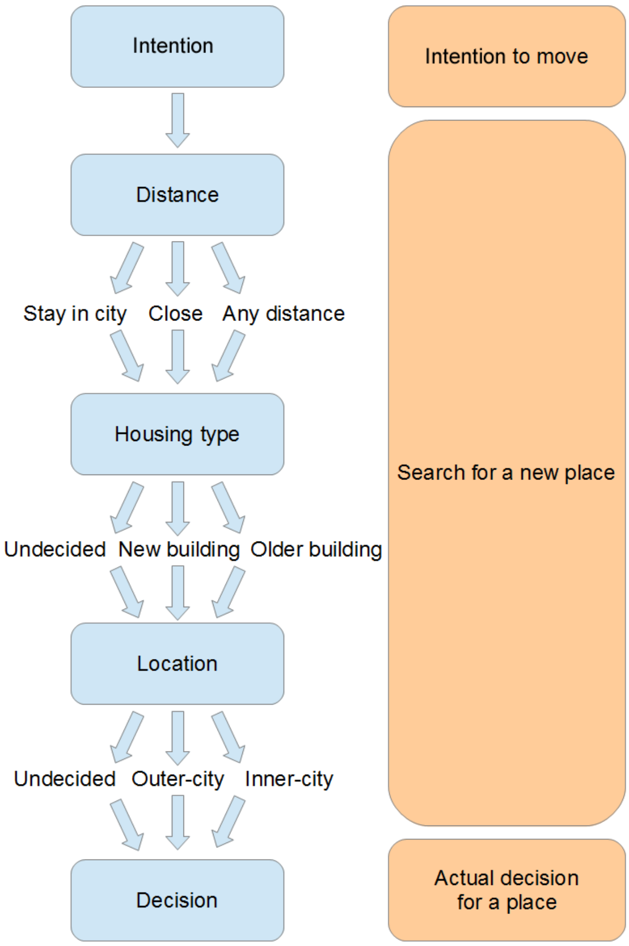

Figure 3.6. Three-stepped search of households for a new dwelling place.

Equation 3.1 shows how the total attractiveness of a city is determined. It is used for the actual decision for a new place.

$$totalA^t = \frac{priceF * priceA^t + quantityF * quantityA^t + qualityF * qualityA^t}{priceF + quantityF + qualityF} * households^t \quad (3.1)$$

$totalA = Total\ attractiveness\ of\ the\ city$
$priceA = Attractiveness\ of\ the\ price$
$quantityA = Attractiveness\ of\ the\ quantity\ of\ supply$
$qualityA = Attractiveness\ of\ the\ quality\ of\ supply$
$priceF = Weighting\ factor\ of\ the\ price$
$quantityF = Weighting\ factor\ of\ the\ quantity\ of\ supply$
$qualityF = Weighting\ factor\ of\ the\ quality\ of\ supply$
$households = Total\ number\ of\ households\ of\ the\ city$

The competition of households for dwelling places is based on social studies. Households that have already been living in a target city have built a social network there (JAIN & SCHMITHALS, 2009; THOMAS et al., 2008). Thus, these households are ahead of the competition for a new dwelling place. Cities change the housing-related factors according to the demand of the households. This process bases on the economic theories of the equilibrium price (MANKIW & TAYLOR, 2004), the price elasticity (HILBER, 2007) and the "hog cycle"(ARENTZ et al., 2010). Urban geographical studies about housing demolition are considered as well (HEIMPOLD & EBERT, 2012). Equations 3.2 and 3.3 explain the development of the supply and the price. The current supply *S* is equal to the demand *D* from two years ago. It reflects the inertial reaction of the housing market to changing demand conditions. The current price *P* is equal to the price from the previous year added to the product of the defined factor price and the difference of the demand and supply of the previous year.

$$S^t = D^{t-2} \quad (3.2)$$

$$P^t = P^{t-1} + (D^{t-1} - S^{t-1}) * factorPrice \quad (3.3)$$

$S = Quantity\ of\ supply$
$D = Quantity\ of\ demand$
$P = Price$
$factorPrice = Strength\ of\ price\ modifications\ caused\ by\ changing\ demand$

Equation 3.4 aims at the quality of houses and describes the rate of demolition of houses which has a positive effect on the average housing quality of a city (DRANSFELD, 2007; HEIMPOLD & EBERT, 2012). The absolute demolition amount is calculated by the product of vacancy and the demolition rate.

$$demolition^t = vacancy^t * demolitionRate \quad (3.4)$$

$demolition = Total\ housing\ demolition$
$vacancy = Total\ vacancy$
$demolitionRate = Relative\ demolition\ rate$

Cities also react on actions taken by neighboring cities according to the cluster theory. For instance, housing supply and prices change due to modifications in neighboring cities (SPIEGEL, 2004). The following equation 3.5 explains how this interaction works and describes the change of supply, which also has an effect on the price.

$$S^t_{change} = \sum_{i=1}^{n} \left(D_i^{t-2} - S_i^{t-2}\right) * factorInfluence \qquad (3.5)$$

$S_{change} = Change\ of\ quantity\ of\ supply$
$n = Number\ of\ neighboring\ cities$
$D_i = Quantity\ of\ demand\ of\ neighboring\ city\ i$
$S_i = Quantity\ of\ supply\ of\ neighboring\ city\ i$
$factorInfluence = Strength\ of\ influence\ of\ neighboring\ cities$

The city's increase of the quantity of housing supply S_{change} at the time t is related to the past quantity of demand and supply D^{t-2} and S^{t-2} of the neighboring city i. The summed value of all cities is weighted by the factor of influence. The resulting change of supply again changes the housing prices. Thus, the competition of communities is reflected and incorporated in ReHoSh.

The concept of ReHoSh is finally implemented in the software "Repast", a Java-based OpenSource toolkit for MAS (RAILSBACK et al., 2006). The model is implemented as a hierarchy of separate classes and contexts, each with its own collections of objects and schedule of their actions. The object-oriented implementation is efficient, with computational time for calibration limited to a couple of minutes – a very short period of time when compared to other complex urban system models (BENENSON & TORRENS, 2004; LEE, 1973; WEGENER, 2011).

3.4.2.4 Calibration and Validation of ReHoSh

One crucial point of ReHoSh is the distinction of new dwellings: "dwellings on free spaces" and "properties". Since 2010, the Association Ruhr (RVR) has been collecting data for potential dwelling areas annually on community scale and implements these figures in the recently developed regional land information system RuhrFIS (REGIONALVERBAND RUHR, 2011). Land values and real-estate prices are taken from the information system of the NRW expert committee for land values (BORISplus.NRW, 2012). Other parameter inputs are derived from the State Office of Statistics (IT NRW, 2013) (Table 3.3). Therefore, it was possible to set up ReHoSh with 2010 as the start year. In contrast, the distinction between calibration and validation data was more complicated because of limited measurements for the potential of new dwelling areas in the Ruhr. Thus, we used official forecasts for the future population development and demographic change (BUCHER & SCHLÖMER, 2003; DANIELZYK, 2006; GRÜBER-TÖPFER et al., 2008), real-estate prices (BORISplus.NRW, 2012) as well as *in situ* land-use provisions (Regionalverband Ruhr, 2011) for reference. In terms of validation accuracy as well as regional generalization ability (COUCLELIS, 2001), we just used the 11 cities as calibration input. The four districts were firstly added in the validation process. Additionally, we used the real-estate analysis commissioned by the Landesbank Baden-Wurttemberg (WESTERHEIDE & DICK, 2010) to approximate the real-estate prices and land values for 1996-2010. In order to estimate the values for the potential dwelling areas, we calculated the ratio of free spaces and properties and their total number in different land-use categories for 2010. We assumed this ratio to be stable in order to use the quantity of the different land uses (IT NRW, 2013) to backcast the number of potential dwelling areas and properties annually. To account for stochastic variability (WEGENER, 2011), we used the mean value of 1,000 simulation iterations.

Table 3.3. Data input of ReHoSh (start year: 2010)

City/ District	Number of households (hh) (*100)			Number of dwellings	Prices (€)		Potential dwelling area (ha)
	1-2 pers, < 45 yrs.+	1-2 pers, ≥ 45 yrs.	≥ 3 pers.		Land*	real estate	
Duisburg	483	1,158	574	259,457	1,880	1,155	158
Essen	740	1,541	613	318,927	2,460	1,244	97
Mülheim a. R.	188	419	222	92,447	1,950	1,232	42
Oberhausen	229	494	255	106,812	1,981	1,106	66
Wesel	339	1,019	496	206,152	1,871	1,190	331
Bottrop	105	267	138	56,120	2,050	1,215	69
Gelsenkirchen	272	663	313	142,506	1,900	879	86
Recklinghausen	562	1,416	758	304,212	1,960	1,191	369
Bochum	506	893	385	192,754	2,030	1,245	98
Dortmund	840	1,420	586	310,814	1,995	1,183	388
Hagen	225	463	237	105,524	1,900	1,093	62
Hamm	149	389	258	85,077	1,876	986	157
Herne	156	422	176	85,373	1,900	1,082	36
Ennepe-Ruhr	330	822	377	170,102	2,321	1,150	211
Unna	291	910	523	191,807	1,999	1,137	375

+ The age of the households is defined by the age of their head.

* Land values includes the costs to develop land from non built-up to built-up area

The calibration of ReHoSh from 2010 to 2025 showed good results regarding the simulation of the development of households, potential dwelling areas, land values, and real-estate prices. Attraction of a city is exclusively defined by the prices and the supply of developable housing areas, which leads to a slight overestimation of the decrease of households. Low real-estate prices and land values lead to a decrease of abandoned property, which again raises the attractiveness of the city. A positive feedback-loop is activated and the number of households increases constantly. Fortunately, ReHoSh seems to be able to capture the oscillating cycles of the housing prices (ARENTZ et al., 2010). Table 3.4 shows the quantitative validation results as mean annual deviations of the total amount in percent observed for the simulated households and prices. Additionally, the percentage of the communities and districts with a deviation lower than 10 % and 5 % are presented. The upshot of the validation run is positive and it can be stated that ReHoSh is able to capture the interaction between household movements in total and price development in the Ruhr at a minimum reliability of 90 %.

Table 3.4. Mean annual deviations (1996-2010) of the total amount in percent observed for the simulated households and prices of the 15 cities and districts of the Ruhr.

City / District	**Households**				**Prices**	
	all	1-2 pers, < 45 yrs.	1-2 pers, ≥ 45 yrs.	≥ 3 pers.	real estate	land
Bochum	2.9	17.6	2.2	7.9	2.97	1.51
Bottrop	9.6	8.2	17.1	6.1	3.35	1.86
Dortmund	1.8	16.1	5.7	7.5	11.38	1.92
Duisburg	2.6	4.7	7.2	5.5	4.86	12.70
Ennepe-Ruhr	1.7	4.9	4.8	5.4	7.66	1.13
Essen	3.3	10.3	5.9	7.9	5.26	3.99
Gelsenkirchen	5.3	11.9	3.7	5.5	10.04	5.02
Hagen	2.2	8.1	5.1	3.0	3.53	1.99
Hamm	7.3	7.9	12.7	5.5	1.94	2.58
Herne	2.6	7.9	11.5	8.6	6.14	1.02
Mülheim a.d.R.	4.1	8.7	8.6	4.3	3.33	1.21
Oberhausen	2.5	7.6	3.1	3.5	4.60	1.68
Recklinghausen	2.1	7.7	6.7	12.5	24.31	3.82
Unna	7.2	7.3	16.3	2.8	6.78	2.04
Wesel	7.3	3.6	16.6	2.5	6.63	3.28
dev. <10%	100	73.3	66.6	93.3	80.0	93.3
dev. <5%	66.6	20.0	20.0	33.3	53.3	86.6

3.5 Cells and Agents – Combining Spatial Pattern and Dynamic Processes

3.5.1 Urban Landscape Configuration in 2025

Based on the urban land-cover pattern 2005, we modeled the spatial growth of the cities and districts in the Ruhr up to 2025. As this study focuses on the combination of spatial and non-spatial simulation of urban growth, we have chosen a simple "business as usual"-scenario (ALCAMO et al., 2006). Figure 3.7 depicts the urban landscape configuration with the chosen adjustments for 2025. One can state that the allocation of urban cells with SVM and UGMr-SVM is strongly tailored to already existing urban areas. Most of the predicted urban areas are found on the edge of the agglomeration and in inner urban free spaces. The map contains large, homogenous regions in the rural hinterland of the agglomeration with persistent non-urban areas. The combination with SVM technique in addition to the use of MC iterations suppresses UGMr's preference for a stochastic allocation of urban cells. In total, UGMr-SVM predicted an urban growth of 3,995 ha, which is ~3 % of the urban area observed in 2005. It must be noted that the model is prone to a quantitative underestimation. However, recent studies have shown that a slight decrease of land consumption in Ruhr due to a slight shift to inner city development in particular is plausible (BBSR, 2012; MUNLV, 2013; REGIONALVERBAND RUHR, 2011; SIEDENTOP & KAUSCH, 2004). Again, the aim of the German federal government claiming a reduction of land take to 30 ha per day until 2030 seems unlikely (BBSR, 2012).

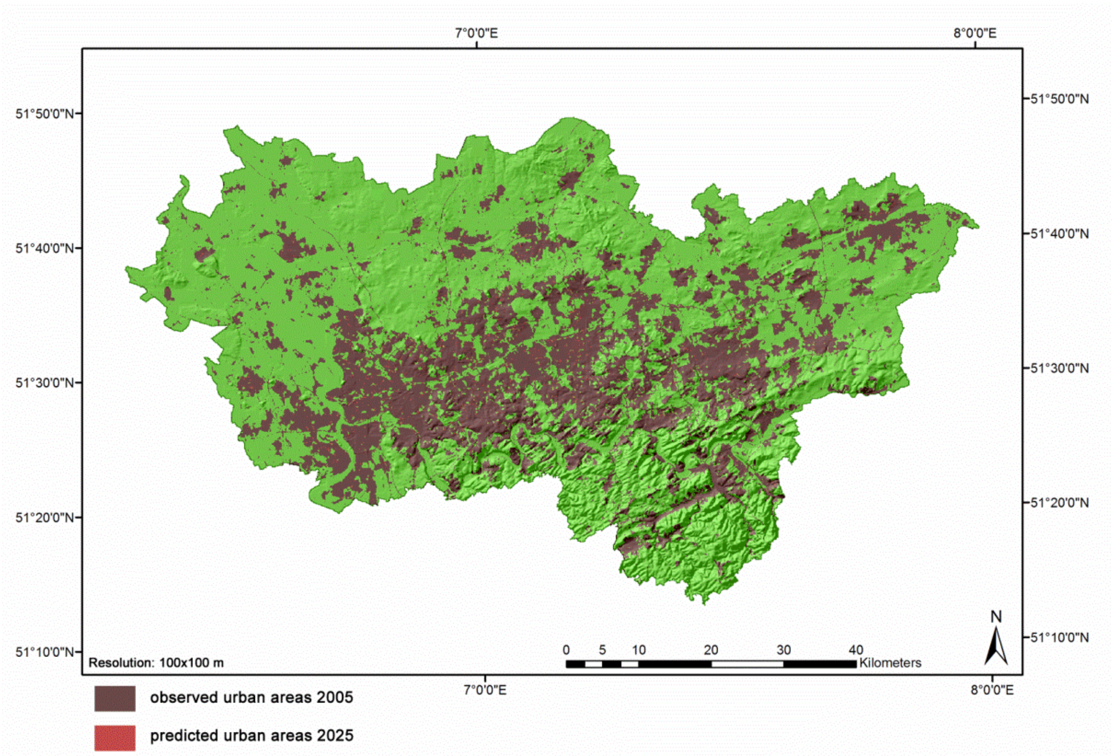

Figure 3.7. The urban landscape configuration of the Ruhr in 2025 predicted by UGMr-SVM.

The dominant predicted growth type is the external growth which simultaneously closes gaps in the existing settlement areas of the Ruhr. While the "spread" coefficient is the main growth impetus in the UGMr-SVM simulation, the dispersive growth and the emergence of new settlements ("breed") are of minor importance. The simulation of the urban landscape configuration in 2025 reveals where newly urbanized areas are most likely to be allocated according to the current trends of urban growth. Again, it has to be stated that UGMr is a purely growth-oriented model. Having a closer look at the specific simulation conditions, the drawback is narrowed. While demolition is an important issue for city planning in the Ruhr, the phenomenon of "urban perforation" (KROLL & HAASE 2010) will not transmit a critical signal at the given study scale of 100 m (BBSR, 2012; HOSTERT, 2007; SIEDENTOP & FINA, 2008).

3.5.2 Urban Landscape Composition in 2025

We added the four districts of the Ruhr to the calibrated adjustments of ReHoSh and started 1,000 simulation runs for 2025 using a plausible "business as usual"-scenario. The results are mean values for the cardinal parameters and features of the non-spatial urban landscape composition. Figure 3.8 shows the results of the aggregated households and land values of three cities and one district. The presented communities are located in the west (Duisburg), the south east (Hagen), the north (Recklinghausen) and the center (Recklinghausen) of the Ruhr. Additionally, the deviations derived from the validation of ReHoSh (Tab. 3.4) are plotted. To enable a comparative analysis, the different measure scales have been indexed by relating the development to ReHoSh's start year 2010.

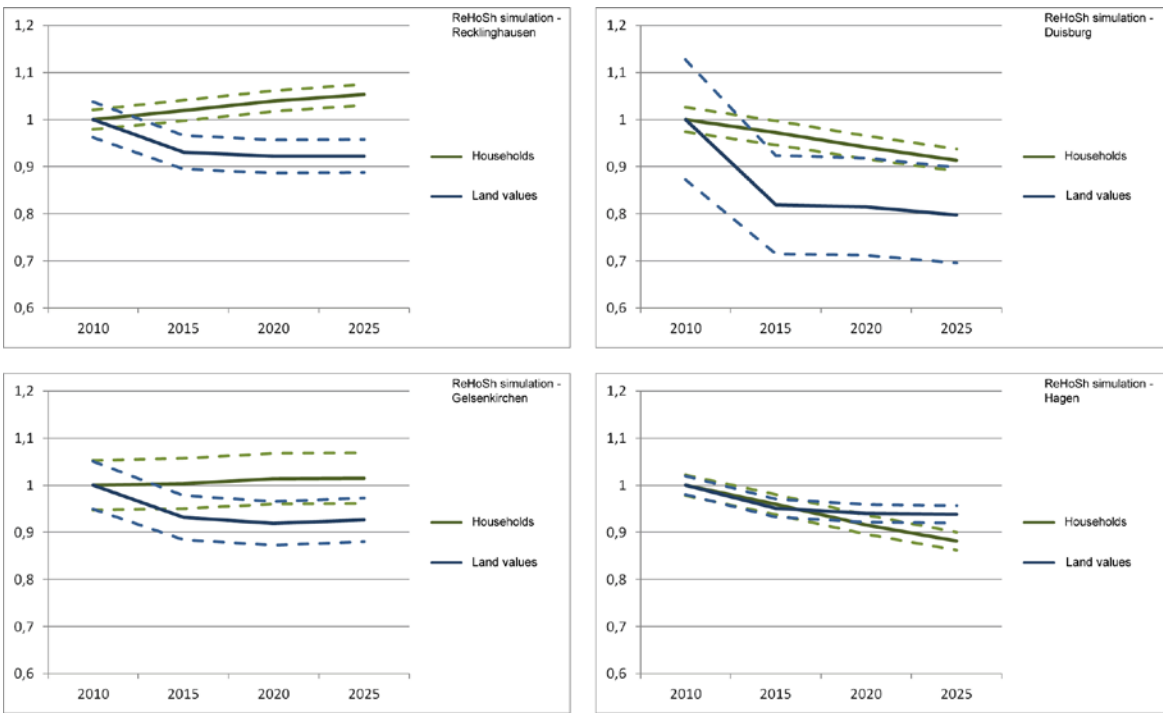

Figure 3.8. Indicated results of the aggregated households and land values (ReHoSh) of Recklinghausen, Duisburg, Gelsenkirchen, and Hagen (clockwise) 2010-2025.

Of note is the trend of local land values. After a steep decrease, a constant level is reached and ends in slight increase. This is due to an overestimation of housing supply by ReHoSh at the beginning of the simulation, which leads to the significant immediate price decrease. Besides, there are interesting differences. Gelsenkirchen and Recklinghausen exhibit a growth in urban areas and in population – both are the only cities/ districts in the simulation with demographical growth – while Duisburg and Hagen show a clear demographic decline. Hereby, Recklinghausen is the only city where the demographic growth rate (+0.5 %, +964 hh/yr) is as high as the one of urban land use (+0.5 %, +64 ha/yr). In comparison to Gelsenkirchen (+0.2 %, +127 hh/yr), its household growth until 2025 is stable and does not show any signs of a decrease. Indeed, that is due to an overestimation in the group of young, small households (+15.6 %, +587 hh/yr). Nevertheless, its high housing supply in the extra-urban regions in combination with a moderate price level (~1950 €/sq m) raises its attraction for this household size type. In contrast, out of the four cities presented, Hagen has the largest decline (-12 %, -730 hh/yr). Even the steep decline in land values is not sufficient to slow population loss. As well as in Duisburg, the peripheral position reduces the catchment area of Ruhr migrants searching for housing spaces near their home region. Referring to the extension of urban land use, it is Duisburg that has the smallest increase of new urbanized areas (+0.4 %, +35 ha/yr). Of course, it is the low supply in free developable land, as a certain fraction of the city's area is occupied by water bodies and industrial land uses.

The results provide insight into possible future trends and into the dynamic of urban shrinkage and growth processes in the Ruhr. In what follows, the focus is on the spatial distribution of the future development of population and prices. For this, the results of UGMr and ReHoSh are loosely coupled (VERBURG et al. 2004b) by applying geostatistical estimation methods for spatial disaggregation (HÄGERSTRAND, 1967; LANGFORD & UNWIN, 1994; MENNIS & HULTGREN, 2005).

3.5.3 Spatial Join of Pixels and Households

In order to join the results of UGMr-SVM and ReHoSh, dasymetric mapping was applied to disaggregate the simulated household numbers of ReHoSh for 2025. The result is a map containing household density estimations for every pixel. The procedure was done for the three household types.

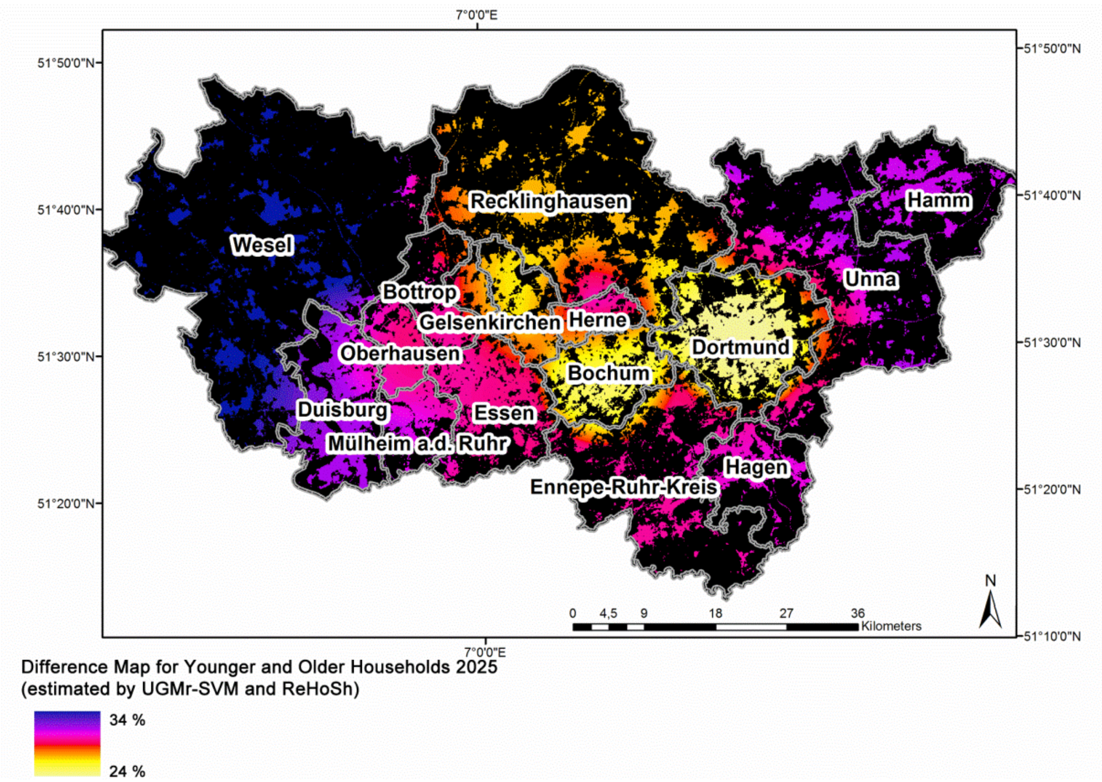

Figure 3.9. Difference map for younger and older households (1-2 persons) 2025.

Figure 3.9 shows the difference map for younger and older households (1-2 persons). The larger the difference, the higher the density of households older than 45 years in comparison to households younger than 45 years in 2025. The largest differences in the calculation of UGMr-SVM and ReHoSh can be found in Wesel. Twenty percent of the total households are younger than 45 years while 54 % are older. The same applies to the two districts in the eastern part of the Ruhr, Hagen and Ennepe-Ruhr, and the peripheral city of Hamm. The cities exhibiting the highest differences are Bottrop and Herne with 32 %. The case of Herne is interesting because it borders the three cities/ districts that distinctly show difference values below the average. In 2010, Herne was the city with the lowest amount of potential dwelling area (Tab. 3.3). Thus, ReHoSh simulated a constant increase of the housing prices, which weakened the demand in the younger household group looking for cheaper dwelling space.

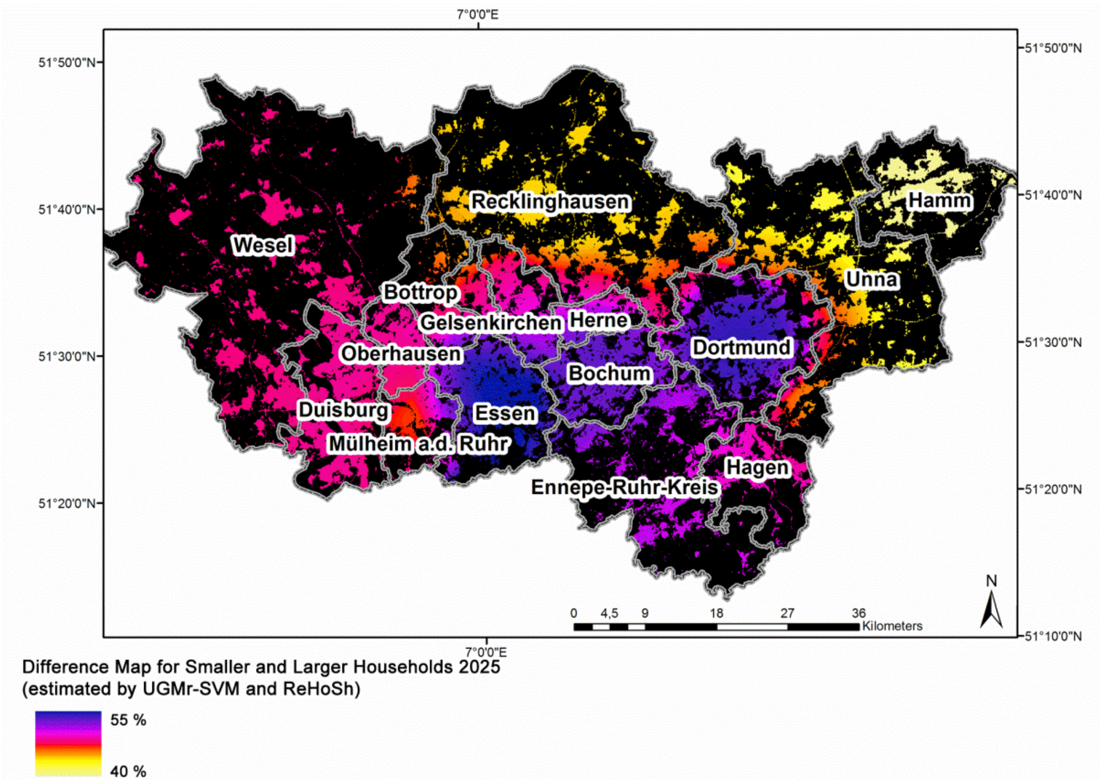

Figure 3.10. Difference map for smaller and larger households 2025.

Figure 3.10 presents another instance of fragmentation calculated by UGMr-SVM and ReHoSh. Here, the relation of all smaller households with 1-2 persons has been contrasted with the relation of households with 3 and more persons. Larger differences are accompanied by higher densities of households with less than 3 persons, relative to households with more than 3 persons in 2025. Interestingly, it seems to be the opposite of figure 3.9. The core cities of Dortmund, Bochum, Gelsenkirchen and Essen exhibit values around 53 %, with the largest differences between the two household size types. In contrast, the three abovementioned districts and the peripheral city of Hamm (40 %) show the smallest differences. The spatial pattern reflects the preference of the larger households, for instance families, for rural areas at the edges of an agglomeration providing space for single-family houses (BBSR, 2012, IT NRW, 2013).

3.5.4 Spatial Join of Pixels and Prices

The main advantage of ReHoSh is the opportunity to forecast land values and real-estate prices based on estimations of interregional household migrations and the corresponding reactions of the cities (cf. 3.4.2.3). The combination with UGMr-SVM makes it possible to depict these prices in a spatial manner. As opposed to the visualization of household developments, no disaggregation method was applied since a homogenous price distribution within a city or a district, respectively, is assumed. A polygon shapefile containing the simulated prices for 2025 on community scale was converted into raster data. Subsequently, the real-estate prices were assigned to the urban areas modeled by UGMr-SVM and the land values were assigned to non-urban areas. To derive trend developments, the same was done for the base data of 2005.

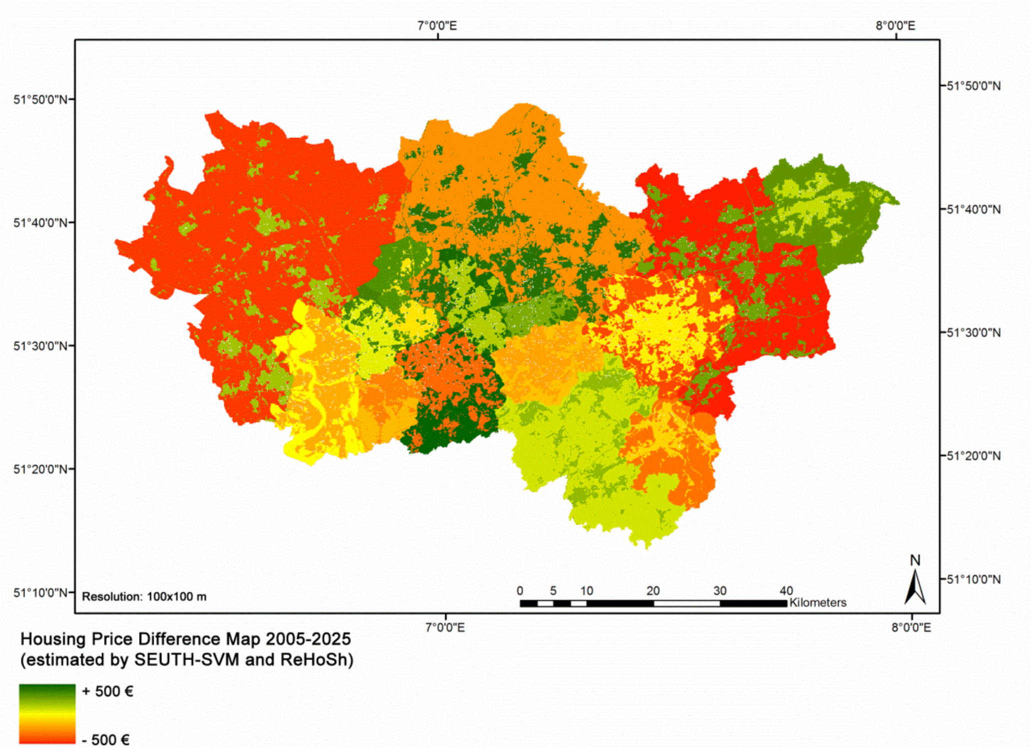

Figure 3.11. Housing price difference map 2005-2025.

Figure 3.11 contains the price difference map 2005-2025 depicting negative and positive trends. A simple reading of the map focuses on the contrast between urban and non-urban areas. There are cities and districts where price development of land and properties proceeded similarly: Bochum (-112€/sq m, -66€/sq m), Duisburg (-80€/sq m, -16€/sq m) and Hagen (-43€/sq m, -160€/sq m) with a decrease, and Hamm (+46€/sq m, +155€/sq m), Gelsenkirchen (+51€/sq m) and Ennepe-Ruhr (+135€/sq m, +16€/sq m) with an increase in real-estate prices and land values. However, there are also contrary developments. Here, the other three rather rural districts – Recklinghausen (+430€/sq m,-130€/sq m), Unna (+147€/sq m,-460€/sq m) and Wesel (+85€/sq m, -350€/sq m) – are distinguished by very high increases in real-estate prices and very high decreases in land values. This is due to the fact that those districts have opposite trends regarding the household types. While they grow in the group of young and small households, those communities lose in the group of the larger households. The rather family-reflecting group is known to be interested in properties on green field sites while younger, smaller households tend to migrate to cheaper properties in the urban core areas (Mielke & Münter, 2008; Rossi, 1980). Hence, the supply of free spaces seems to be larger than the demand, and the land values in 2025 are smaller than that of 2005. The cities of Bottrop (30€/sq m, +212€/sq m), Oberhausen (-8€/sq m, +249€/sq m) and Essen (-223€/sq m, +591€/sq m) in the southwestern and south-central part of the Ruhr exhibit the inverted case: increasing land values and decreasing real-estate prices. All household types are decreasing in these communities. Thus, the pattern is typical for shrinking cities simulated with ReHoSh in general. While urban core areas are less frequently demanded, a slight migration trend towards the suburban regions can be assessed.

3.6 Conclusion

It was the aim of this paper to contribute to the application of AI techniques for simulating urban development in shrinking city regions. A CA and an MAS have been set up, validated, and loosely coupled to address the simultaneously ongoing processes of urban sprawl and urban decline of the Ruhr. The region's specific settlement structure is characterized by large urban areas solely divided through administrative borders. The scattered rural districts complete the image of a challenging study region in terms of organizational hierarchies, migration flows, and heterogenic housing markets.

At first, the popular urban growth model SLEUTH was applied to model urbanization in the Ruhr for 2025 in a spatially explicit fashion. With UGMr, we used the modified version of the CA defining its growth parameters by MRV and two land-cover data set. An SVM-based probability map including the impact of driving forces on the allocation of new urban areas was combined with the exclusion layer of SLEUTH. Hence, the model could be guided and its stochastic variability regarding the emergence of urban cells depressed. The application of SVM additionally delivered insights into the most important factors driving the local urbanization suitability. Thus, the CA provided a theoretical foundation. The importance of distance-related variables over socioeconomic or demographic variables in the SVM model was clear. Geophysical variables were not useful to select areas suitable for urban growth with SVM. The validation indices for UGMr-SVM showed good values around 0.8 (ROC and Kappa) and 0.93 (MRV). The urbanization rate predicted by UGMr-SVM is ~3 % of the urban area observed in 2005. The 30 ha goal for the daily land consumption in Germany is rather unlikely to be achieved. The dominant predicted growth type is the external growth which simultaneously closes gaps in the existing settlement areas of the Ruhr.

As SLEUTH is a pure growth model, an MAS model was constructed to simulate behavioral processes such as intraregional population migration and housing price changes. ReHoSh incorporates different household agents interacting with the 15 communities so that complex, dynamic supply-demand processes based on individual as well as common economic decisions could be captured. Additionally, different housing types and pricing situations were constructed. The simulation of general household trends with ReHoSh achieved deviations under 10 % for all communities. Notably, two-thirds of the communities in the group of the smaller sized households still depict this accuracy level. Land and real-estate prices deviate less than 10 % in nearly all of the modeled cities and districts. The results of ReHoSh are spatially implicit and aggregated on community level. Simple spatial joins were used to couple both AI results loosely for visualizing the spatial distribution of future trends of different household types and housing prices. The resulting spatial patterns of the age and size households on the one hand, and price differences between inner and extra urban areas on the other, can serve as valuable inputs for future regional planning; especially when urban development is discussed in the context of multifarious demographic change and preceding urban growth. The spatial pattern reflected the preference of family households for rural areas and the preference of younger households for the agglomeration's core areas. A price difference map 2005-2025 depicted negative and positive trends and the contrast between the development of land values and real-estate prices.

The study has shown how AI methods can help understand changes of the spatial configuration and non-spatial composition of urban systems. A drawback of the approach is the lacking connection between UGMr-SVM and ReHoSh. As a next step, we could move from the loose and indirect combination to a strong and direct coupling of both AI methods. For this purpose actors and factors, pixels and people must already be linked during the modeling process. In doing so, the impacts of rather non-spatial decision making would be extended in a spatially explicit manner.

4 Sprawling Cities and Shrinking Regions – Forecasting Urban Growth in the Ruhr for 2025 by Coupling Cells and Agents

Source: RIENOW, A., STENGER, D. & MENZ, G. (2014): Sprawling Cities and Shrinking Regions – Forecasting Urban Growth in the Ruhr for 2025 by Coupling Cells and Agents. ERDKUNDE – Archive for Scientific Geography, doi: 10.3112/erdkunde.2014.02.02

Abstract

In the 20th century, the environment of Central Europe was shaped by an extensive growth of urban areas leading to sprawling agglomerations. While the cities' morphological growth is still proceeding, a second major trend is emerging nowadays: urban decline. Accordingly, the polycentric agglomeration of the Ruhr (North Rhine-Westphalia, Germany) simultaneously faces a demographic decline and a physical extension. The modeling of both trends is essential in order to estimate their social and ecological impacts. Among urban land-use models are artificial intelligence techniques like cellular automata (CA) and multi-agent systems (MAS). While CA focus on discrete spatial entities, MAS are well-suited to capture individual decision making. This study presents an approach dealing with the integration of both complementary methods: the coupling of the MAS ReHoSh (Residential Mobility and the Housing Market of Shrinking City Systems) and the CA SLEUTH. SLEUTH is one of the best-assessed spatially-explicit urban growth models applied in numerous studies all over the world. Here, the CA will be guided by support vector machines in order to enhance its modeling performance. ReHoSh is a newly implemented MAS catching the interactions between stakeholders of housing markets and the development of potential residential areas in a declining urban environment. The concept of semi-explicit urban weights is introduced transferring the probable dwelling demand as results of individual decision making into the cellular environment. The CA-MAS combination is calibrated in order to mine the urban future of the Ruhr. Beside a "business as usual"-scenario, two further scenarios of changing housing preferences are simulated for 2025. They reflect the dissemination of sustainable thinking among stakeholders and the steady dream of owning a house in sub- and exurban areas. The created total probability maps clearly influence the future rates of SLEUTH. The CA is successfully provided with scenarios resulting in different extents of the Ruhr's urban area for the year 2025: 136,007 ha ("business as usual"), 134,285 ha ("sustainable thinking"), and 140,141 ha ("dream of owning a house"). The spatial impacts are visualized with the concept of urban DNA and a digital petri dish. Here, it becomes obvious that a sprawled pattern of the cities of the Ruhr is just prevented in the scenario "sustainable thinking".

4.1 Introduction

In the 20th century, the environment of Central Europe was shaped by an extensive growth of urban areas leading to sprawling agglomerations. The cities' morphological growth still proceeds but is superimposed by a second major trend nowadays: urban decline. Administrations are confronted with an aging population, demographic shrinkage, a loss of economic power as well as an ever-increasing land consumption (COUCH et al. 2005; HAASE et al. 2012; KABISCH et al. 2006; SCHWARZ et al. 2010; SIEDENTOP & FINA 2008). The modeling of both trends is essential for estimating their social and ecological impacts (LAMBIN et al. 2001). Since the beginning of the millennium, artificial intelligence (AI) techniques have found their way into land-system simulation addressing the complex challenges of transitions in urban areas as open, dynamic systems (ALCAMO et al. 2006; BATTY 2005; BENENSON & TORRENS 2004; VERBURG et al. 2004a). Among those AI techniques are cellular automata (CA) and multi-agent systems (MAS) (BATTY 2005; BENENSON & TORRENS 2004; SILVA & WU 2012). Instead of applying statistical relations, CA and MAS both use bottom-up modeling paradigms to alter the states of their entities. While CA focus on discrete spatial entities, MAS are well-suited to capture individual decision making. In terms of geosimulation, agents are often defined as an abstract entity, which is autonomous, intelligent, mobile, and adaptive. They work as a community rather related to each other through communication and actions than through fixed spatial links (BENENSON & TORRENS 2004; KOCH & MANDL 2003; NARA & TORRENS 2005; RAUH et al. 2012; SILVA & WU 2012; STEVEN et al. 2002; SUDHIRA et al. 2005; VALBUENA et al. 2008). In doing so, agents are characterized by proactive behavior – the most important quality distinguishing MAS from CA (LOIBL & TOETZER 2003). CA, however, are one of the most popular AI simulation tools. This is mainly due to the facts that their handling is relatively simple and that they are able to catch a complex pattern development at the same time. Urban CA are often defined by (1) a raster lattice representing the spatial context, (2) a set of states associating a cell with a certain land-use type, (3) neighborhoods influencing their spatial configuration, and (4) transition rules regulating the conversion of a cell state with every (5) time step (BARREDO et al. 2003; BATTY & XIE 1997; CLARKE et al. 1997; HILFERINK & RIETVELD 1999; LANDIS 2001; TOBLER 1975; WHITE & ENGELEN 1993; WU & YEH 1997).

The characters of CA and MAS are complementary in terms of their focuses (land conversion vs. population dynamics), status changes (neighborhood determination vs. independent behavior alteration), mobility of their entities (fixed vs. mobile), and representations (geographic vs. socio-economic factors). Hence, their integration promises to accomplish "the need for hybrid systems" (WU & SILVA 2010, 253) as a leading challenge in land-system science so that pixels can be linked with people (GEOGHEGAN et al. 1998; LESSCHEN et al. 2005; RINDFUSS & STERN 1998; SILVA 2011; VERBURG et al. 2004b; WOOD & SKOLE 1998). Studies dealing with the coupling of CA and MAS often focus on specific urban-change phenomena like gentrification and segregation (BENENSON et al. 2005; NARA & TORRENS 2005), suburbanization (LOIBL & TOETZER 2003), rural-settlement development (LIU et al. 2013), transport systems (BECKMANN et al. 2007), spatial planning (LIGTENBERG et al. 2001), and urban expansion (SUDHIRA et al. 2005; ZHANG et al. 2010). HAASE et al. (2012) describe a concept for coupling CA and MAS in order to operationalize social science knowledge regarding urban shrinkage in Leipzig (Germany). Accordingly, RIENOW & STENGER (2014) apply the urban growth CA SLEUTH and the MAS ReHoSh (Residential Mobility and the Housing Market of Shrinking City Systems) focusing on demographic decline in the Ruhr. The results are loosely coupled for analyzing the development of different household types and housing prices in terms of their spatial distribution. This paper presents a further integration of both AI techniques. Instead of a loose coupling approach, the MAS results will be transferred into the CA. Hence, the urban growth model is directly affected by the outcomes of the Ruhr's housing market simulation executed with the MAS.

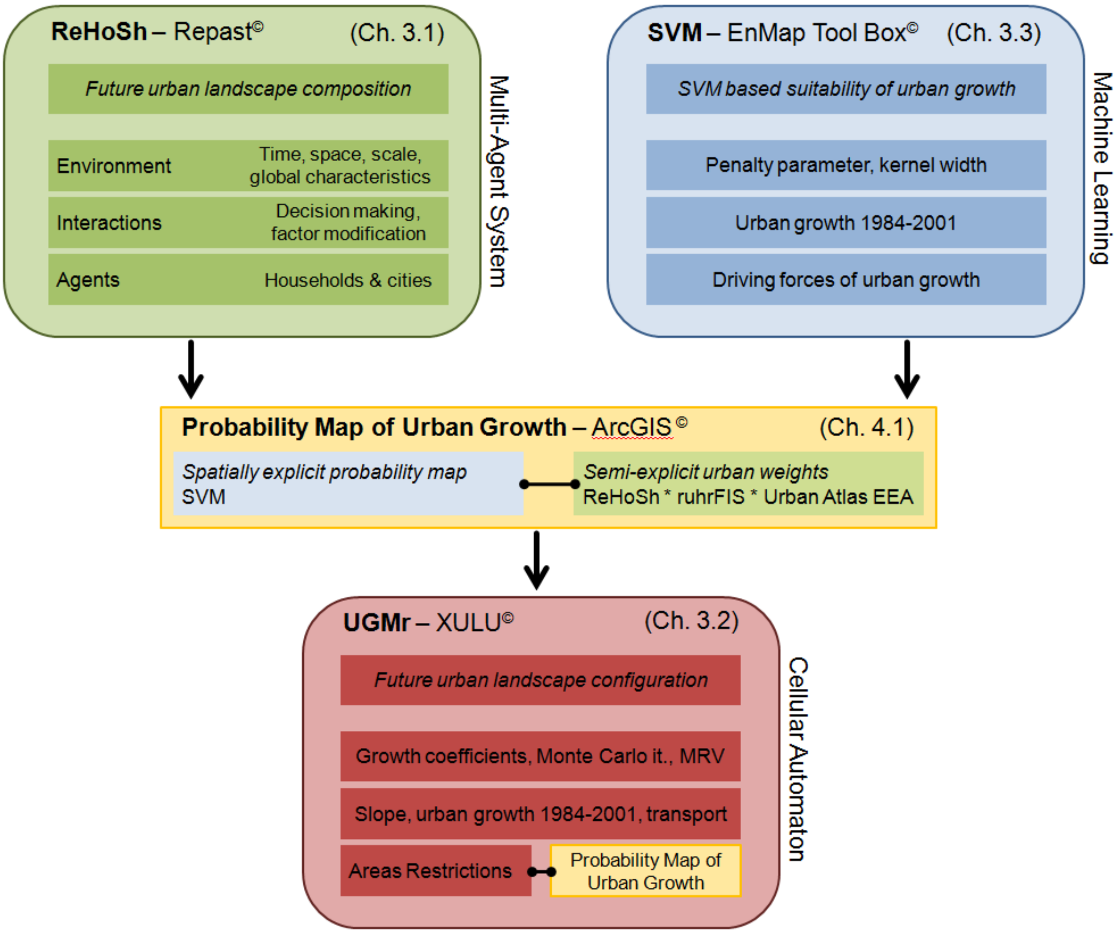

Figure 4.1. Framework for coupling SLEUTH UGMr (CA) and ReHoSh (MAS) including the software and parameters used in the study.

Figure 4.1 depicts the workflow of the study. The implemented CA is a modified version of SLEUTH Urban Growth Model (UGMr) (red) (CLARKE et al. 1997, GOETZKE 2012). SLEUTH is one of the best assessed urban CA (CHAUDHURI & CLARKE 2013) and has been applied in numerous urban-growth studies all over the world (CLARKE et al. 1997; GOETZKE 2012; RAFIEE et al, 2009; SILVA & CLARKE 2005; WU et al. 2008). In order to enhance the modeling performance of SLEUTH UGMr, the CA will be guided by a probability map of urban growth derived by the application of support vector machines (SVM) (blue) (CORTES & VAPNIK 1995). The MAS compartment of the coupling framework is represented by ReHoSh (green). ReHoSh catches the interactions between stakeholders of housing markets and the development of potential residential areas in a declining urban environment (RIENOW & STENGER, 2014). The concept of semi-explicit urban weights is introduced and implemented to transmit the results of ReHoSh to SLEUTH UGMr. For this purpose, the semi-explicit urban weights are combined with the SVM-based probability map of urban growth (yellow). Scenarios are to be developed which are meant to shed light on the future land conversion of the Ruhr in the context of changing housing preferences. They illustrate two possible future trends for 2025: On the one hand, the dissemination of sustainable thinking among stakeholders and on the other hand the steady dream of owning a house in sub- and exurban areas. Subsequently, the results will be analyzed by means of the concept of urban DNA (cf. 4.4.3).

In a nutshell, the research directives of this study are:

1. The development and formalization of a concept transferring individual decision making into the cellular context.
2. The implementation of an integrated CA and an MAS with regard to the growth and shrinking conditions of the Ruhr.
3. The application of the coupled CA-MAS model to mine the future of the Ruhr assuming three scenarios for the year 2025.

The paper is structured as follows: Section 4.2 introduces the research area and the applied data. The subsequent sections explain the implementation of the models ReHoSh and SLEUTH as well as the SVM application (Section 4.3). Section 4.4 presents the concept and the approach for coupling the AI models. Additionally, the results of three future scenario calculations are analyzed. The advantages and limitations of linking pixels and people in urban system modeling will be discussed critically in section 4.5. Finally, it provides a short conclusion and gives an outlook for future research.

4.2 Study Area and Data

4.2.1 The Ruhr – Urban Growth meets Urban Shrinkage

The Ruhr lies in North Rhine-Westphalia in the western part of Germany (Fig. 4.2). The region is named after the eponymous tributary of the Rhine. The Ruhr extends from the Lower Rhine basin in the west to the Westphalian Plane in the north and the Rhenish Massif in the south. In general, 15 cities form the biggest agglomeration (1,150 people p. km^2) in Germany. The biggest are – in descending order – Dortmund, Essen, Duisburg and Bochum; each with a population of 370,000 to 580,000 (REGIONALVERBAND RUHR 2011).

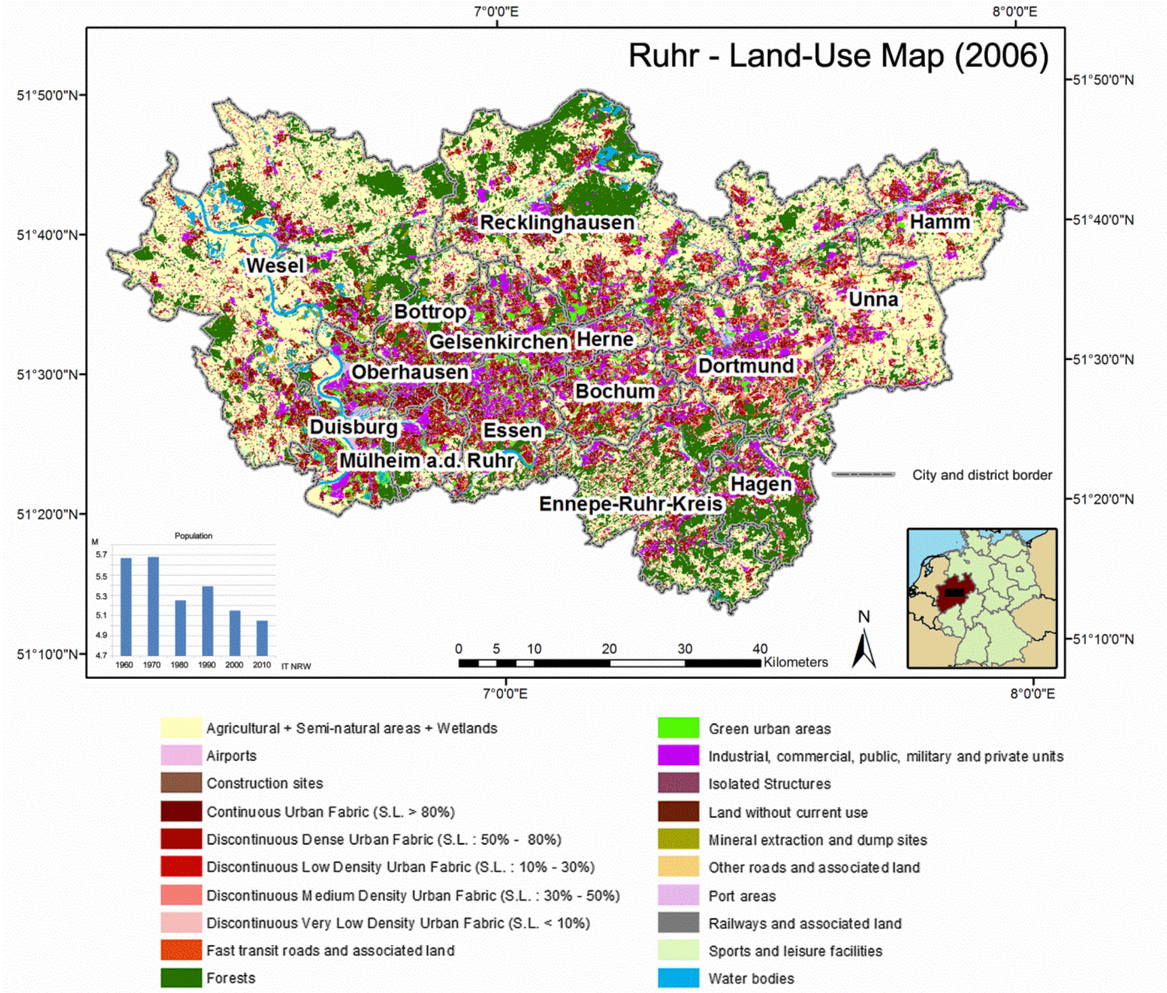

Figure 4.2. Land-use map (2006) with cities and districts of the Ruhr (North Rhine-Westphalia, Germany) (Source: EEA).

Like all other members of the "rusty" fellowship (COUCH et al. 2005), the Ruhr faces a demographic decline, an aging population, high unemployment rates, an incipient brain drain and a lack of incentives to attract prosperous companies of the service sector, especially the "new economy" (COUCH et al. 2005). The overall population decreased from 5.4 M to 5.1 M between 1996 and 2010, one in ten persons is unemployed and the amount of employees working in the service sector has been stagnating at 72 % for twelve years. Therefore, the Ruhr can be characterized as a stagnating old center of employment (BLOTEVOGEL 2006; COUCH et al. 2005; DANIELZYK 2006; GRÜBER-TÖPFER et al. 2008; HOYMANN et al. 2012).

The drawn shrinking tendencies contrast with the physical extension of the Ruhr's cities. Between 1975 and 2005, the agglomeration grew around 37,022 ha with a total urban area of 94,990 ha to 132,012 ha. Its physiognomic pattern is dispersed and concentrated on the urban fringes, on the exurban areas as well as on small and middle towns in the cities' functional field of gravity (HOMMEL 1984; SIEDENTOP 2006). There are several causes compensating the demographic decline such as the demographic trend towards smaller households, the fiscal competition between communities, planning routines (greenfield instead of brownfield development), and the preference for low-density housing (HIRSCHLE &

SCHÜRT 2008; MIELKE & MÜNTER 2008; SIEDENTOP & FINA 2008). The question of how the ongoing demographic and job shrinkage will affect the future urban pattern of the Ruhr is complex and interfered by the structural transformations. An "urban perforation" of the spatial pattern as observed in Eastern Germany with large demolition areas in the centre has not been observed yet. However, a parallel occurrence of sprawl and shrinkage in spatial terms cannot be excluded for the near future (SCHWARZ et al., 2010; SIEDENTOP & FINA, 2008; WIECHMANN & PALLAGST, 2012).

4.2.2 The Data – Discretizing the Surface of the World

For this study, a time series of LANDSAT data of the years 1975, 1984, 2001, and 2005 is provided by the monitoring project NRWPro. The data sets were classified with a mixed approach of supervised classification algorithms and knowledge-based decision trees. The data simply distinguish between "urban" and "non-urban areas", where "urban" is defined with a degree of imperviousness of min. 25 %. The post-classification validation achieved an accuracy of >85 %. In order to balance the spatial resolution and the spatial extent of the Ruhr, a grid resolution of 100 m is used. The detailed classification process is presented by GOETZKE et al. (2006) and SCHOETTKER (2003). For the calibration of SLEUTH, the data of 1984 constitutes the base year and the data of 2001 constitutes the reference year. For the validation of SLEUTH, the data of 1975 is the base year and the data of 2005 is the reference year. Finally, in order to train the SVM model, the urban growth detected in the classified LANDSAT data between 1984 and 2001 is used.

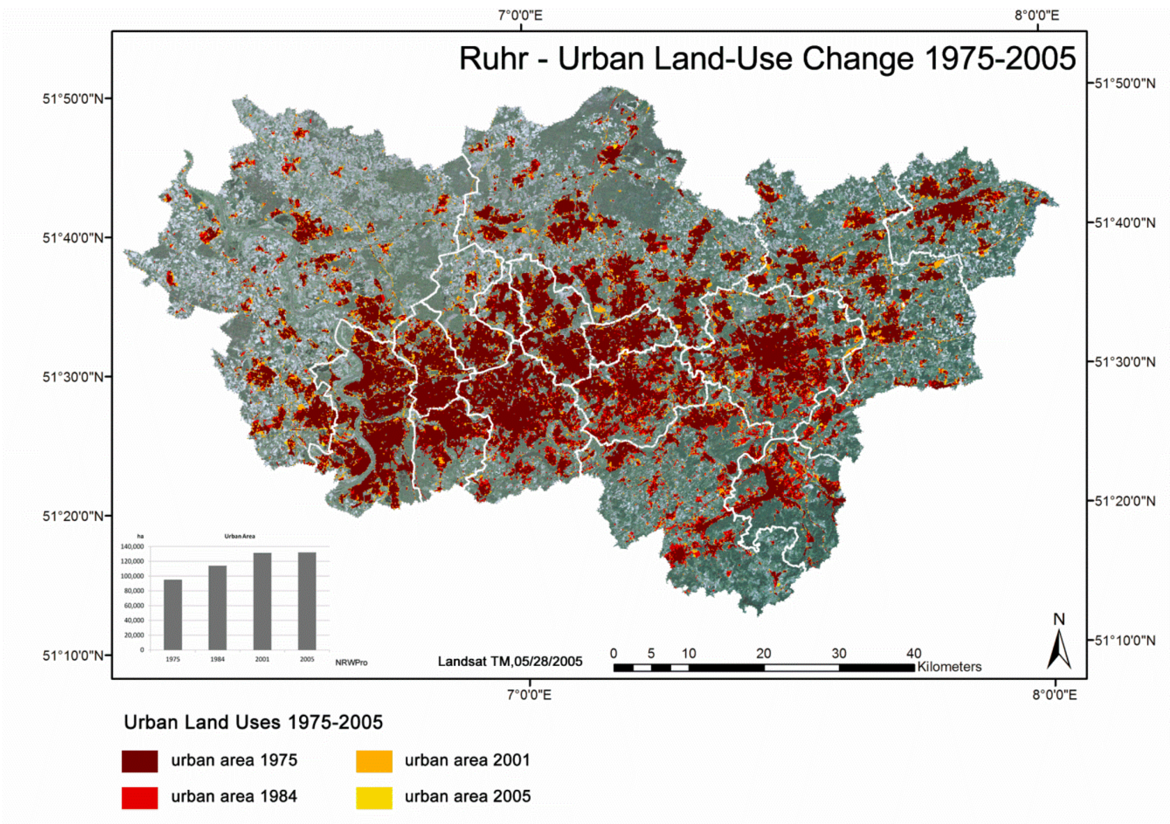

Figure 4.3. Urban growth of the Ruhr 1975-2005 (derived from NRWPro data set).

Knowledge about potential residential areas on green- and brownfields is crucial for the implementation of ReHoSh. With RuhrFIS, a regional land-information system was established aggregating their municipal indications for potential residential areas for the whole Ruhr (REGIONALVERBAND RUHR 2011). Actual land values and real estate prices are taken from the information system of the NRW Expert Committee for Land Values (BORISPLUS.NRW 2012). The remaining parameter inputs (Tab. 4.3) are derived from the State Office of Statistics (IT NRW 2013).

While the NRWPro data is spatially explicit, the RuhrFIS data are aggregated on community level. In order to combine ReHoSh and SLEUTH, a data set is needed which mediates between both levels. The Ruhr has to deal with 53 zonings of different semiotic systems, coverage dates, and durability. Instead of zonings, we apply the international inter-comparable European Urban Atlas of the European Environment Agency (EEA) (Fig. 4.2). The European Urban Atlas is part of the local component of the GMES/Copernicus land monitoring services and based on high-resolution earth observation data. It has a minimal mapping unit of 0.25 ha and provides 21 urban land-use and land-cover classes for the reference year 2006 (LAVALLE et al. 2002; MEIRICH 2008). Even though the potential residential areas are not directly demarcated, it assigns adequate land uses.

Table 4.1 gives an overview of the different land-use semiotics regarding associated land uses of potential residential areas on greenfields. RuhrFIS defines agricultural areas, meadows, pastures, forests, and other as potential residential areas on greenfields (REGIONALVERBAND RUHR 2011). Accordingly, those pixels were extracted from the urban atlas containing one of these land-use classes. In order to ensure the consistency of the applied data sets, the extracted pixels were compared to the NRWPro data set of 2005. Those being classified as "urban" in NRWPro were discarded. The same holds true for pixels containing "forest". The development of forest is rarely implemented in the regional planning but has a high fraction on the total land cover (GOETZKE 2012; REGIONALVERBAND RUHR 2011; SIEDENTOP & KAUSCH 2004; ULMER et al. 2007). The maintenance of the class forest would weaken the significance of the map of potential residential areas.

Table 4.1. Potential residential areas (greenfields) and their semiotics.

NRWPro*	RuhrFIS	EEA Urban Atlas
Impervious surface <25 %	agricultural areas; meadows; pastures; forests; other	construction sites; land without current uses; green urban areas; agricultural, semi-natural areas, wetlands;

*NRWPro is funded by the Ministry for Climate Protection, Environment, Agriculture, Nature Conservation and Consumer Protection of the State of North Rhine-Westphalia

4.3 The Artificial Intelligence of Cells and Agents

4.3.1 ReHoSh – MAS Simulation of Urban Decline

The MAS ReHoSh focuses on the dynamic of interregional housing markets implying the development of population patterns, housing prices, and housing supply in shrinking city agglomerations (Fig. 4.1). Its object-oriented implementation in the MAS open-source software Repast© (RAILSBACK et al. 2006) provides ReHoSh with a computational time limited to a couple of minutes – a very short period compared to other complex urban system models (BENENSON & TORRENS 2004; LEE 1973; WEGENER 2011).

Table 4.2. Key elements, definitions, and prerequisites of ReHoSh.

Key Elements	Definition	Prerequisites
Agents	Households (hh)	Constant hh size; unlimited knowledge of all possible residential places; limitation to housing-related factors
	Cities and districts (cs)	Developers, landholders, and the administration at once
Interactions	Intention, search, decision	Hh move or stay; hh compete with hh
	Modification of housing-related factors	Cs react to hh; cs compete with cs
Environment	Time	Discrete, one year per simulation step
	Space	15 cs of the Ruhr
	Scale	Residential (decision making); community level;
	Global characteristics (e.g. economy, demography)	Prices rise and fall linearly; inelastic price behavior; constant demographic decrease; exclusion of other exogenous impacts

Table 4.2 presents the key elements of ReHoSh and the main prerequisites of the simulation framework (COUCH et al. 2005; HANNEMANN 2002; MACAL & NORTH 2010; SCHLEGELMILCH 2009). The households and the cities themselves represent the agents. Here, the cities contain not only administrative structures but also other stakeholders of the real-estate markets like entrepreneurs, landholders, and developers. The most important driving factor of ReHoSh is the proactive search of the household agents for a new housing place (Fig. 4.4) (AJZEN 1985; BENENSON & TORRENS 2004; KALTER 1997; KOCH & MANDL 2003; ROSSI 1980). It consists of a three-step-pattern from intention to move (I) to the search procedure (II) to the decision for a new place (III). The households can compete with each other. Those who have already been living in a target city have built a social network there and are ahead (JAIN & SCHMITHALS 2009; THOMAS et al. 2008). Furthermore, the decisions of the household agents stimulate the city agents to react.

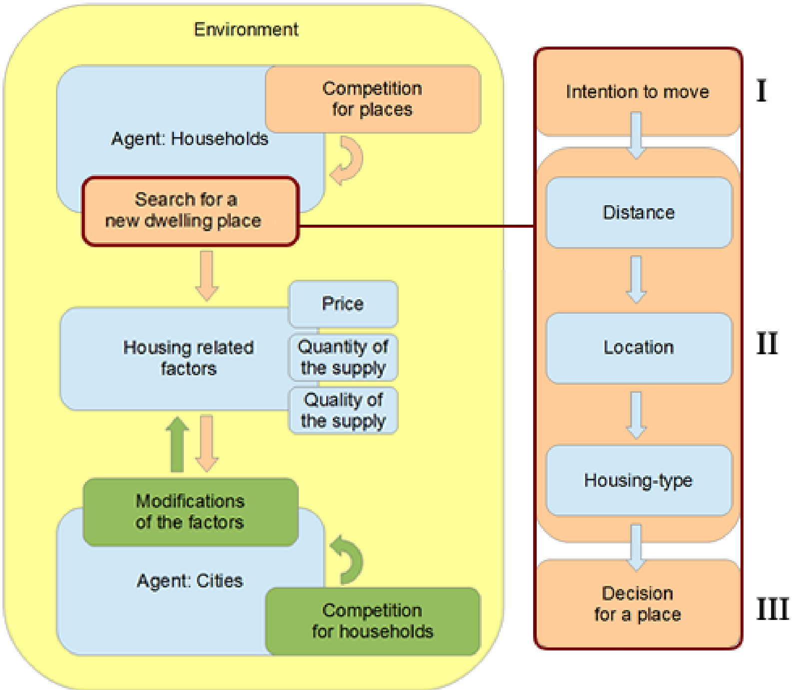

Figure 4.4. Main concept of ReHoSh showing the agents, the interactions, and the key factors (left). Three-stepped search of households for a new dwelling place (right).

The city agents can change the housing-related factors according to the economic theories of the equilibrium price (MANKIW & TAYLOR 2004), the price elasticity (HILBER 2007) and the "hog cycle" (ARENTZ et al. 2010). Thus, the current housing supply is equal to the demand from two years ago (ARENTZ et al. 2010). It reflects the inertial reaction of the housing market to changing demand conditions. An absolute demolition amount is calculated influencing the housing quality of a city (DRANSFELD 2007; HEIMPOLD & EBERT 2012). Additionally, cities can raise their supply as a reaction to neighboring cities' behavior (SPIEGEL 2004). Equation 4.1 shows how the total attractiveness of a city is determined. It is used for the actual decision for a new place. Beside the price level and the quantity of the supply, the qualitative attractiveness of the supply is calculated. This is related to the vacancy and demolition rates of a community. Hence, the feedback loop between household migration, vacancies, and price development is incorporated.

$$totalA^t = \frac{priceF * priceA^t + quantityF * quantityA^t + qualifyF * qualityA^t}{priceF + quantityF + qualifyF} * households^t \quad (4.1)$$

$totalA = Total\ attractiveness\ of\ the\ city$
$priceA = Attractiveness\ of\ the\ price$
$quantityA = Attractiveness\ of\ the\ quantity\ of\ supply$
$qualityA = Attractiveness\ of\ the\ quality\ of\ supply$
$priceF = Weighting\ factor\ of\ the\ price$
$quantityF = Weighting\ factor\ of\ the\ quantity\ of\ supply$
$qualityF = Weighting\ factor\ of\ the\ quality\ of\ supply$
$households = Total\ number\ of\ households\ of\ the\ city$

Table 4.3 contains the implementation values of ReHoSh for the start year 2010. The calibration and validation procedure of ReHoSh is described in RIENOW & STENGER (2014). It makes use of official back- and forecasts for the future population development, demographic change, real estate prices, and land-use provisions (BORISPLUS.NRW 2012; BUCHER & SCHLÖMER 2003; DANIELZYK 2006; GRÜBER-TÖPFER et al. 2008; IT NRW 2013; REGIONALVERBAND RUHR 2011; WESTERHEIDE & DICK 2010). It can be stated that ReHoSh is able to capture the interaction between household movements in total and price development in the Ruhr at a minimum reliability of 90 % (RIENOW & STENGER, 2014).

Table 4.3. Base data input of ReHoSh for the year 2010 (Source: BORISPLUS.NRW 2012; IT NRW 2013; REGIONALVERBAND RUHR 2011).

City / District	Households				Prices	
	all	1-2 pers, < 45 yrs.	1-2 pers, ≥ 45 yrs.	≥ 3 pers.	real estate	land[i]
Bochum	2.9	17.6	2.2	7.9	2.97	1.51
Bottrop	9.6	8.2	17.1	6.1	3.35	1.86
Dortmund	1.8	16.1	5.7	7.5	11.38	1.92
Duisburg	2.6	4.7	7.2	5.5	4.86	12.70
Ennepe-Ruhr	1.7	4.9	4.8	5.4	7.66	1.13
Essen	3.3	10.3	5.9	7.9	5.26	3.99
Gelsenkirchen	5.3	11.9	3.7	5.5	10.04	5.02
Hagen	2.2	8.1	5.1	3.0	3.53	1.99
Hamm	7.3	7.9	12.7	5.5	1.94	2.58
Herne	2.6	7.9	11.5	8.6	6.14	1.02
Mülheim a.d.R.	4.1	8.7	8.6	4.3	3.33	1.21
Oberhausen	2.5	7.6	3.1	3.5	4.60	1.68
Recklinghausen	2.1	7.7	6.7	12.5	24.31	3.82
Unna	7.2	7.3	16.3	2.8	6.78	2.04
Wesel	7.3	3.6	16.6	2.5	6.63	3.28
dev. <10%	100	73.3	66.6	93.3	80.0	93.3
dev. <5%	66.6	20.0	20.0	33.3	53.3	86.6

[i] Land values includes the costs to develop land from non built-up to built-up area

4.3.2 SLEUTH – A Cellular Automaton of Urban Growth

CLARKE's UGM, for the main part identified as SLEUTH, was developed by CLARKE et al. in 1997. It is an acronym of its initial input factors slope, land use, exclusion, transport, and hillshade (Fig. 4.1). The exclusion information is optional, but it enables the incorporation of regional planning information – e.g. conservation areas – and probability maps. Five growth coefficients (dispersion, breed, spread, slope, road gravity) define the four growth rules of UGM: spontaneous growth, reflecting the random emergence of new urban areas, new spreading center growth, edge growth depicting urban sprawl, and road-influenced growth (Fig. 4.5).

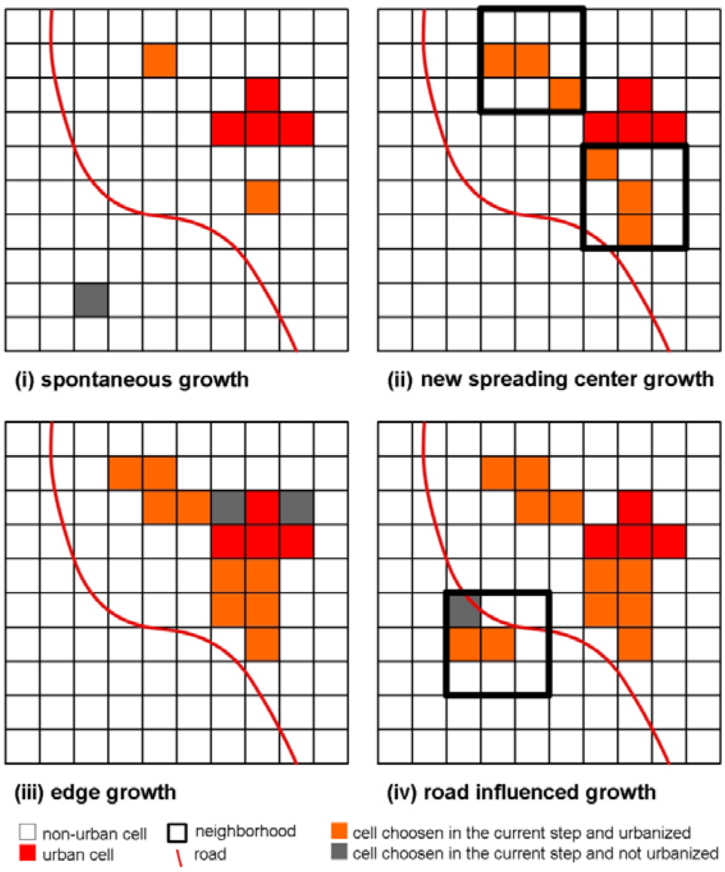

Figure 4.5. Growth types of a growth cycle in UGM.

One growth cycle represents one year and consists of the four aforementioned subsequent rules. Each selected new urban cell is compared to the local slope and exclusion information as well as a random value. The growth coefficients are defined during the calibration process of UGM. Every parameter combination of the particular growth coefficients between values of 0 to 100 is tested until their optimal balance is assessed. Since an assessment of all possible parameter combinations would be far too time-consuming, the calibration procedure is performed in several steps, starting with a coarse evaluation and refining the results in several intervals (Goetzke, 2012; Rafiee et al., 2009; Wu et al., 2008). By using a cut-off value (cf. 3.3), the map can be transformed into a binary land-use map (Verburg, 2006). GOETZKE (2012) modified UGM to reduce the urban land-use data input from five to two (UGMr, Urban Growth Model reduced). He replaced the standard calibration evaluation method by multiple resolution validation (MRV) (PONTIUS et al. 2008) and implemented it into XULU©. XULU (eXtendable Unified Land Use Modeling Platform) is a JAVA-based modeling environment developed at the University of Bonn (GOETZKE & JUDEX, M. 2011; SCHMITZ et al. 2007). Goetzke (2012) applied UGMr for a simulation run for the whole region of NRW and compared it with the original UGM defining the growth coefficients with Lee-Sallee index (Clarke et al., 1997). Besides showing that UGMr achieved a slightly higher accuracy than UGM, he was able to demonstrate that UGM achieves a better performance when using the same growth coefficients defined in the calibration run for UGMr (Goetzke, 2012). Although Dietzel & Clarke (2007) defined another Optimal SLEUTH metric consisting of seven metrics apart of the Lee-Sallee index, the calibration with MRV still has the advantage that just one metric is needed. However, while the performance of UGMr is very high the modeling process still is strongly influenced by stochastic decisions resulting in a variable spatial pattern. Besides, it gives no information about the human and ecological forces driving the local suitability of urban growth. Here, the combination of UGMr with a suitability map is a reasonable approach for guiding the CA (MAHINY & CLARKE 2012; RIENOW & GOETZKE, 2014).

4.3.3 SVM – Support Vector Machines as CA Conditioner

RIENOW & GOETZKE (2014) have shown that the application of SVM augments the quantity and the allocation performance of UGMr, suppresses its stochastic variability, and increases its simulation certainty (Fig. 4.1). SVM are based on a machine-learning concept developed for solving classification problems (CORTES & VAPNIK 1995); VAPNIK 1998). To put it simply, an SVM model is a binary classifier labeling a sample of empirical data by constructing the optimal separating hyperplane (DRUCKER et al. 1999; GUO et al. 2005; HUANG et al. 2010; MOUNTRAKIS et al. 2011; OKWUASHI et al. 2009; VAPNIK 1998; XIE 2006). The main advantage of SVM is the option to transform the model in order to solve a non-linear classification problem without any prior knowledge. The input vectors are re-projected to a higher-dimensional space in which they can be classified linearly (BURGES 1998; VOGEL 2011; WASKE et al. 2010). The outline of the constrained optimization problem is

$$\min_{\mathrm{w,b}} \frac{1}{2}\|w\|^2 + C \sum_{i=1}^{n} \xi_i \qquad \text{subject to } y_i(\langle w, x_i \rangle + b) - 1 \geq 0 \text{ for } i = 1, \dots, n \tag{4.2}$$

y_i = class label (e.g. urban growth, non-urban growth)
x_i = data point in n-dimensional feature space
w = normal to the separating hyperplane
b = bias
C = penalty parameter
ξ_i = slack variable

The first part of the objective function tries to maximize the margin between the classes and the second part minimizes the classification error. The optimization problem is solved by outlining it in a dual form derived from constructing a Lagrange function according to the Karush-Kuhn-Tucker optimality condition (BURGES 1998).

In our case, the feature space is a raster layer stack consisting of ecological and social driving forces of urban growth (EEA 2006; MIELKE & MÜNTER 2008; SIEDENTOP FINA 2010; VERBURG et al. 2004a). It consists of distance variables, density measurements as well as dasymetric maps (Tab. 4.4). Thus, the layer stack reflects the "location-specific characteristics" of every cell (VERBURG et al. 2004a, 146). Admittedly, the risk of incorrect cross-level deductions in terms of ecological fallacy is reduced but it is not yet totally eliminated (Robinson 1950).

Table 4.4. Variables[+] selected for SVM model.

Name	**Description**	**Rank[*]**
Distance-related variables		
DistAirport	Cost-weighted distance (CWD) to next international airport	5
DistCity	CWD to next city > 25.000 inh.	3
DistHighway	CWD to next highway exit	2
DistRailway	CWD to next railway station	1
DistRiver	Euclidian distance to next river	6
HighwayBuffer	500 m buffer to highways	n.i. [X]
Geophysical variables		
Elevation	Elevation above sea level (m)	11
Soil depth°	Vertical extent of soil layer (cm)	n.i.
Soil type°	Soil type defined by grain size (nominal)	n.i.
Soil quality°	Agricultural appropriateness (from [temporary] "not usable" to "very good agricultural location")	n.i.
Waterlogging°	Waterlogging type (from "low" to "very high")	n.i.
Water table	Depth of complete water saturation below ground (cm)	n.i.
Socioeconomic variables		
Income	Inverse distance-weighted (IDW) average income per month in district 1991	n.i.
Jobs	IDW number of jobs 1991	4
Land Price	IDW land value 1990	7
NetDwellArea	IDW per capita net dwelling area 1990	8
Unemployment	IDW unemployed per population 1991	9
Demographic variables		
Cars	Number of cars in district; Density Function (10 km kernel) DF	n.i.
Migration25-50	Difference between in- and out-migration per settlement of the group aged 25 to 50	n.i.
PopDens	Population density 1984; DF	10

+ Data sources are ATKIS (German federal topographic information system) and the State Office of Statistics.

*Rank according to the forward feature selection.

X Not included.

° Dummy coded.

The SVM model is constructed with the software package imageSVM© developed at the Humboldt University Berlin (Waske et al., 2010). It is calibrated with a training data set containing 4,000 pixels of urban growth and non-urban growth. In order to avoid spatial autocorrelation, a minimum distance between equal pixels of 1 km is used (LESSCHEN et al. 2005). The probability map is calculated according to Platt's probability function (PLATT 1999; WU et al. 2004).

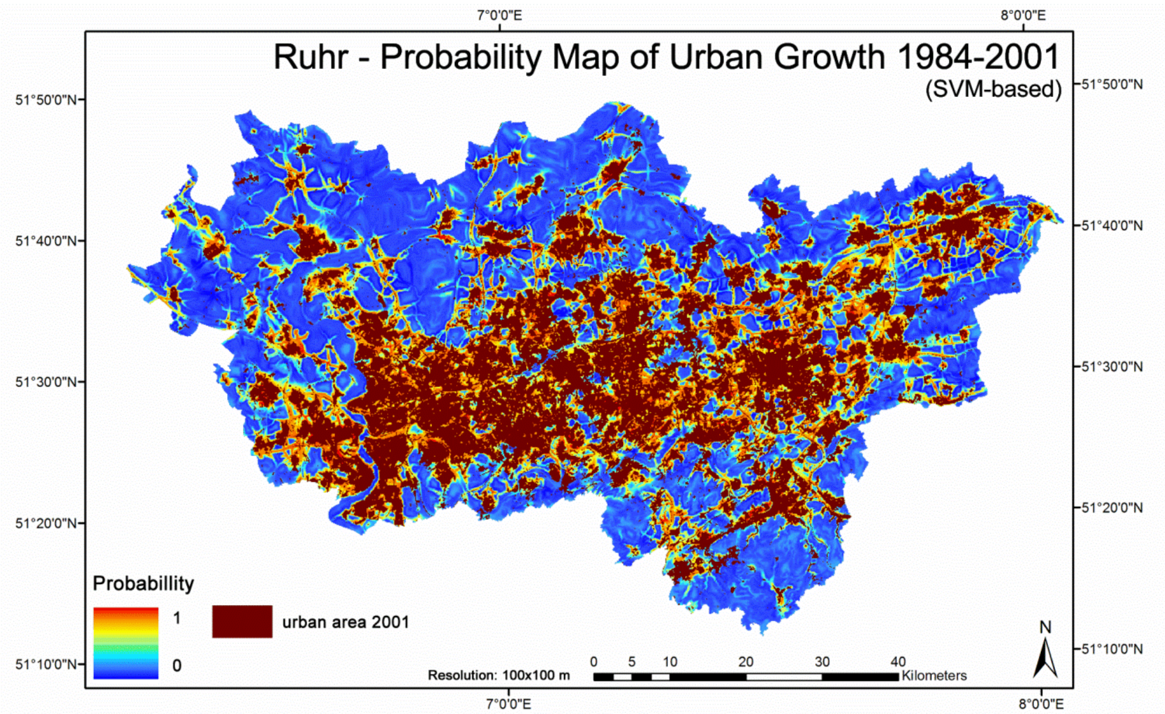

Figure 4.6. SVM probability map of urban growth 1984-2001.

Subsequently, the SVM probability map of urban growth (Fig. 4.6) is combined with the exclusion layer of UGMr (RIENOW & GOETZKE, 2014). The CA is calibrated and by using 100 Monte Carlo iterations (MC), the stochastic nature of the CA is further depressed. A probability of 33 % is used as cut-off value to transform it into a binary land-use map (RAFIEE et al. 2009; WU et al. 2008). At this level, the certainty of UGMr-SVM is reliable in terms of stochastic variability (AERTS et al. 2003; LANGFORD & UNWIN 1994; WEGENER 2011). The calibrated growth coefficients of UGMr-SVM are presented in table 4.5. The achieved validation results are on a very good level regarding the probability performance (ROC), in comparison with randomness (Cohen's Kappa), the quantity estimations ($\varkappa_{histo}$), the allocation ability ($\varkappa_{loc}$), as well as the fuzziness of urban growth (MRV) (LAUF et al. 2012a; MESSINA et al. 2008; PONTIUS et al. 2004; RUIZ et al. 2012; RYKIEL 1996).

Table 4.5. Growth coefficients and validation results 1975-2005 of UGMr-SVM.

		UGMr-SVM
Growth Coefficients	Slope	90
	Dispersion	3
	Breed	4
	Spread	4
	Road	80
	Cut-off value	33%
Accuracy Assessment	$F_{t\ Calibration}$*	0.96
	$F_{t\ Validation}$	0.93
	ROC	0.79
	Kappa	0.80
	$\varkappa_{loc}$	0.93
	$\varkappa_{histo}$	0.87

* F_t is the mean factor of agreement over all resolutions of the MRV

4.4 Coupling Cells and Agents for Modeling the Urban Future

4.4.1 Weighting Urban Growth with Agents

The implementation of SVM reduces the drawback of UGMr regarding the "black-box"-like calculation of urban growth rates. By using factors driving the local urban-growth suitability, the CA is provided with a kind of theoretical foundation (BRIASSOULIS 2000). Yet, the growth coefficients of UGMr determine the amount of new urban cells to be allocated with every growth step. They are based on historical information and set as constant. There is the possibility of an UGMr specific self-modification option assuming a non-linear, s-curve growth type (CLARKE et al. 1997). A relation to dynamic state changes in the coupled human-environment is not incorporated. Hence, conditions and constraints on the macro-level are as much neglected as decisions and their realizations on the micro-level. ReHoSh is developed for catching the behavior alteration of its stakeholders affecting future construction rates and local housing preferences. The quantity of potential new dwellings is dependent on individual decision making beyond the discrete dimension of a pixel. The spatially implicit information must be disaggregated as spatially explicit advice and demand guideline for UGMr. For mitigating between the poles of demand and supply, pattern and process, society and space, as well as pixel and people, we introduce the concept of semi-explicit urban weights. We define semi-explicit urban weights as the simulated dwelling supply varying on community level assigned to cells being in line as potential residential areas. Thus, the probability of new housing constructions is disaggregated from the community level and scaled up to area units containing relevant land uses.

The ReHoSh simulation was carried out with a "business as usual"-scenario updating actual conditions for the year 2025. The modeled supply of residential areas $S_{sim(j)}$ is divided by the potential residential areas of 2010 $S_{pot(ij)}$. It represents the semi-explicit urban weights $P_{uw(ij)}$ for a cell *i* in a community *j*.

$$P_{uw_{ij}} = \frac{S_{sim_j}}{S_{pot_{ij}}} \tag{4.3}$$

The results are assigned to the selected land-use classes of the urban atlas (cf. 4.2.2). Afterwards, the map is merged with the SVM probability map. Hence, the total probability of urban growth of a cell *i* in a community *j* is $P_{total(ij)}$

$$P_{total_{ij}} = \frac{P_{SVM_i} + P_{uw_{ij}}}{2} \tag{4.4}$$

where $P_{SVM(i)}$ are the SVM-based probabilities derived from the location-specific characteristics for a cell *i* . Fig. 4.7 presents the map containing the semi-explicit urban weights (a) and the total probability of urban growth (b).

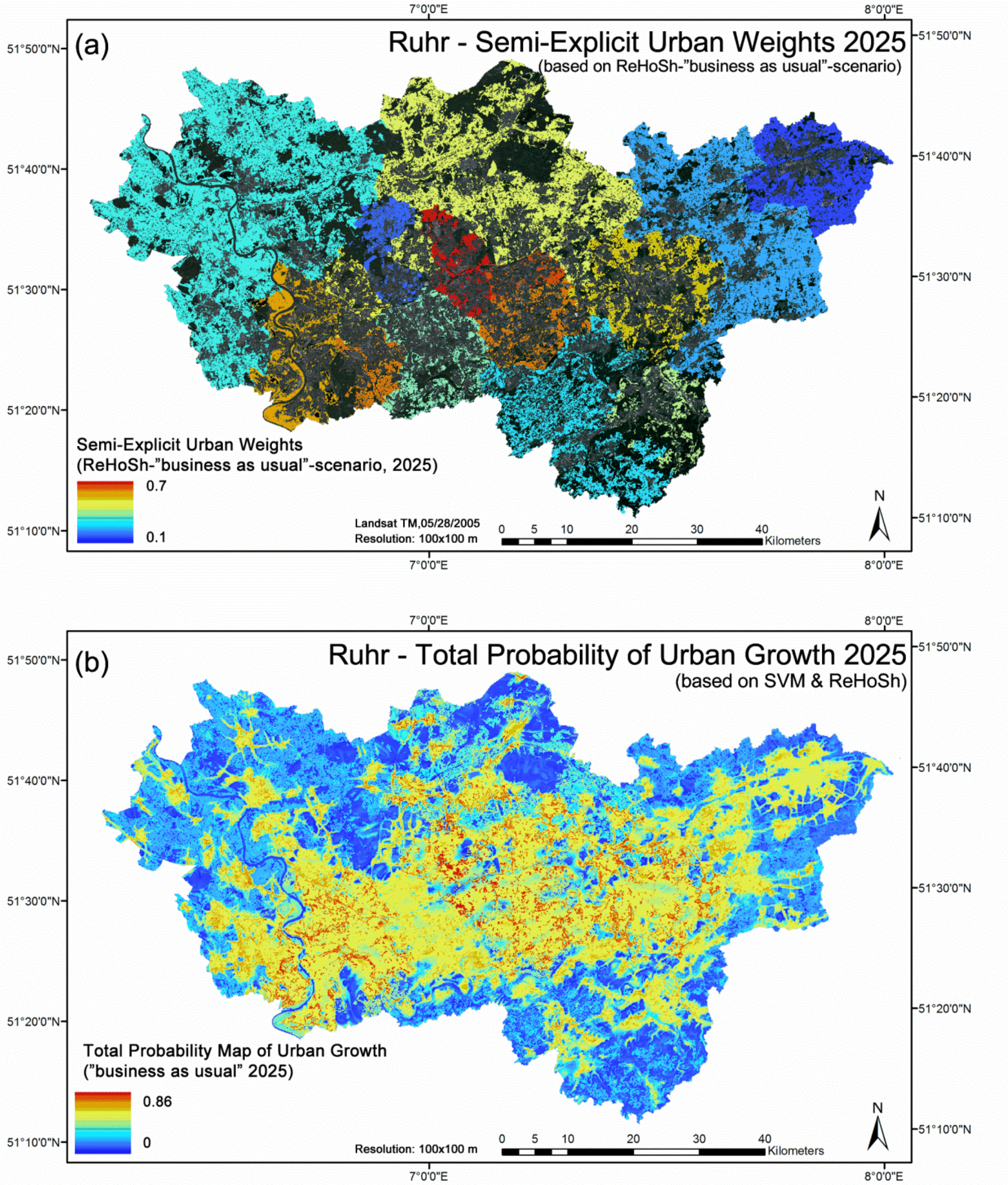

Figure 4.7. (a) Map of semi-explicit urban weights ("business as usual"). (b) Total probability of urban growth ("business as usual").

The value range of the semi-explicit urban weight values is lower than that of the SVM probabilities (Fig. 4.6). In order to maintain the calibrated growth rate of 3,995 ha in the "business as usual"-scenario for the year 2025 and the proportion of the growth types, the CA coefficients of UGMr were adjusted empirically with the factor 10 (Tab. 4.5).

4.4.2 Three Future Scenarios of the Ruhr

The household preferences of ReHoSh are the set screws to implement different scenarios of major trends in the political and economic framework constraints. The scenarios follow the four criteria defined by ALCAMO et al. (2006): relevance, credibility, legitimacy, and creativity. Beside the "business as usual"-scenario, which has already been elaborated on above, two further scenarios called "sustainable thinking" and "dream of owning a house" are created. Both outline a change of the housing preferences whereas the initial impulse for a behavior alteration could be thought of governmental subsidizations like the reintroduction of the "Eigenheimzulage", changing tax burdens, or rental caps (HIRSCHLE & SCHÜRT 2008; MIELKE & MÜNTER 2008). The first scenario reflects the "30 ha directive" set by the German Federal Government pursuing the reduction of daily land conversion to settlement and traffic areas (HOYMANN et al. 2012). The scenario assumes that people are animated to implement the sustainable handling of the limited resource land. The other scenario "dream of owning a house" addresses the subsidization of the steady wish of families to own a house in sub- and exurban areas. It captures the development of new settlement areas consisting of semi-detached buildings as one of the key drivers of urban sprawl in Germany (DITTRICH-WESBUER 2008; HIRSCHLE & SCHÜRT 2008; MIELKE & MÜNTER 2008; SIEDENTOP & FINA 2008). Three scenarios are feasible as the number is "adequate but not overwhelming, brief but not oversimplifying" (XIANG & CLARKE 2003: 899). However, it must be stated that the "business as usual" should not be regarded as the most probable one. It is just a linear prediction of the current states based upon historic information for a complex urban system where business is never usual.

Table 4.6. Preference (%) of dwelling type by different household groups (undecided/ new building / existent building).

	"Business as usual"	"Sustainable thinking"	"Dream of owning a house"
1-2 pers, < 45 yrs.[+]	1.0/ 0.5/ 98.5	1.0/ 0.5/ 98.5	1.0/ 0.5/ 98.5
1-2 pers, ≥ 45 yrs.	5/ 2.5/ 92.5	1.0/ 1.5/ 97.5	7.5/ 5.0/ 87.5
≥ 3 pers.	5.2/ 2.6/ 92.2	1.0/ 1.8/ 97.2	7.7/ 5.1/ 87.2

[+] The age of the households is defined by the age of their heads.

Table 4.6 depicts the preferences of the different household types in the three scenarios. The preferences of a minority (1-2 pers, < 45 yrs) are set as constant. The preferences for existent dwellings in the group of family reflecting households as well as in the biggest group (1-2 pers, ≥ 45 yrs.) are increased by +5 % for "sustainable thinking" and decreased by -5 % in "dream of owning a house". All other parameter settings of ReHoSh like the migration probability of the different household types, their preferred distance, or the demolition and vacancy rates of the different cities are maintained.

4.4.3 Modeling Urban Growth by Coupling CA with MAS

After the simulations have been executed, one can observe an overall decrease of household numbers in the Ruhr for the year 2025. The general trend of demographic decline simulated by the MAS can be observed with slight deviations in all scenarios and is covered by recent forecasts (GRÜBER-TÖPFER et al. 2008; SIEDENTOP & FINA 2008). Table 4.7 includes the P_{uw} values (Eq. 4.2) for every community of the Ruhr in the three scenarios for 2025.

Table 4.7. Semi-explicit urban weights calculated by ReHoSh for the year 2025.

	Change of household numbers (%)	**Semi-explicit urban weights**		
	"Business as usual"	"Business as usual"	"Sustainable thinking"	"Dream of owning a house"
Bochum	-3.6	0.47	0.13	0.98
Bottrop	-10.1	0.13	0.04	0.51
Dortmund	-1.7	0.42	0.13	0.91
Duisburg	-8.6	0.45	0.11	0.96
Ennepe-Ruhr	-1.4	0.22	0.05	0.68
Essen	-6.0	0.87	0.23	0.97
Gelsenkirchen	+1.5	0.74	0.24	0.96
Hagen	-11.8	0.24	0.06	0.70
Hamm	-13.2	0.11	0.04	0.32
Herne	-3.9	0.55	0.15	1.00
Muelheim a.d.R.	-11.3	0.48	0.11	0.95
Oberhausen	-5.5	0.41	0.11	0.96
Recklinghausen	-5.3	0.40	0.10	0.91
Unna	-3.3	0.20	0.04	0.49
Wesel	-4.3	0.23	0.06	0.61

The household numbers decrease in all scenarios in the range of the depicted "business as usual scenario". The conversion of land proceeds in all scenarios. Two cities, Essen and Gelsenkirchen, are simulated to convert most of their potential residential areas already in the "business as usual"-scenario. Here, the difference to the scenario "sustainable thinking" is comparatively higher than the actual changes in the preferences for new dwellings (Tab. 4.6). Other than the cities of Hamm and Bottrop as well as the four rural districts, all cities exclusively convert their potential residential areas in the scenario "dream of owning a house".

The ReHoSh-scenarios of changing housing preferences were transmitted to UGMr-SVM by using the total probability maps. The growth coefficients of the CA adjusted for a ReHoSh-"business as usual"-scenario (cf. 4.3.3) were maintained for the other two scenarios. The same holds true for the cut-off value of 33 after 100 MC. Figure 4.8 presents the scenario results of the coupled CA-MAS model for the Ruhr in 2025. While urban areas have had an extent of 132,012 ha in 2005, it is 136,007 ha in 2025 in the "business as usual"-scenario. The "sustainable thinking"-scenario reduced the growth rate to 2,273 ha to an extent of 134,285 ha in 2025. The "dream of owning a house" evokes a rate of 8,129 ha and an extent of 140,141 ha. Those cells urbanized in the scenario with the lowest growth rate ("sustainable thinking") are also chosen in the other two scenarios. Only a few cells are just simulated as "urban" in one single scenario. One can see that the free spaces between neighboring urban cells are the first areas to be urbanized (Fig. 4.8, "sustainable thinking"). Higher growth rates which are depicted in the other two scenarios lead to a more extensive urban land conversion even in rather remote areas.

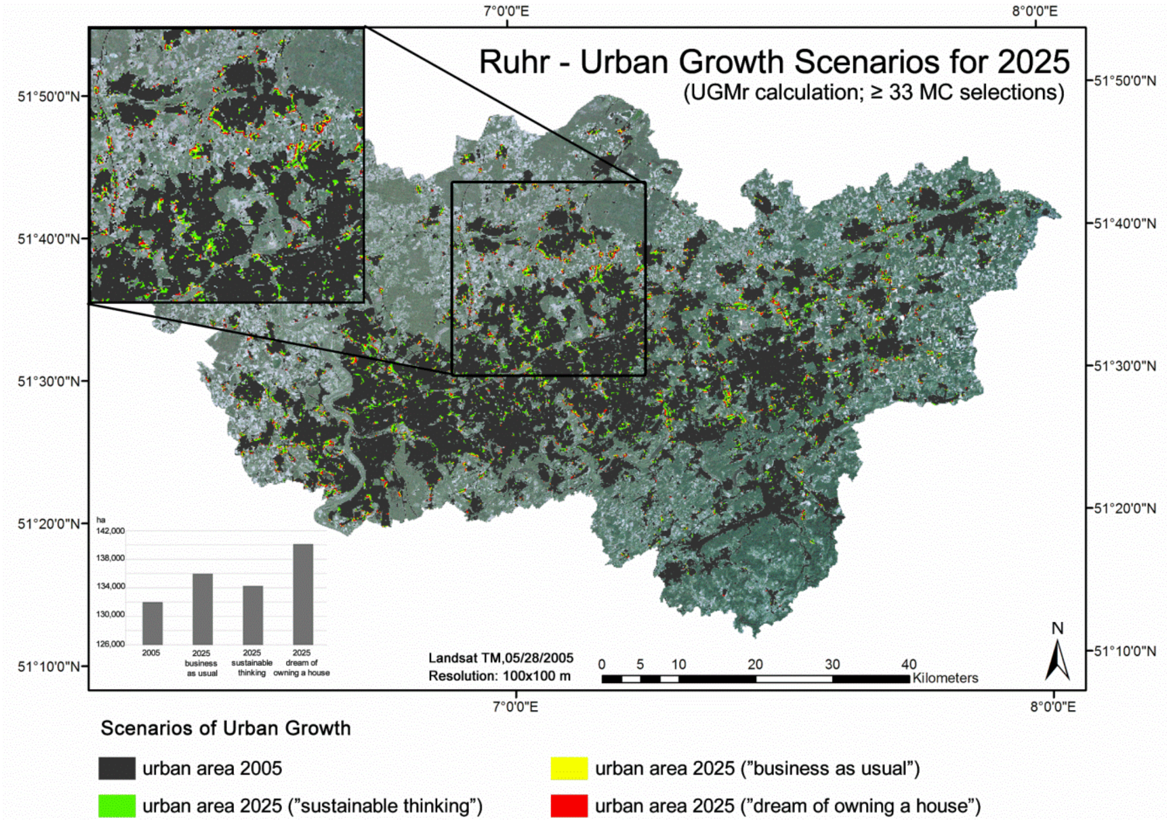

Figure 4.8. Three scenarios of urban land-use configuration of the Ruhr in 2025.

The question of how the scenarios influence the spatial extension of the Ruhr's urban growth will be analyzed with the concept of urban DNA (SILVA 2004). Analogous to the biological DNA, it postulates fundamental elements that are common to each urban area and determine their future growth pattern (SILVA & CLARKE 2005). Accordingly, geographical problems are assessed in a uniform representation of space with a homogenous geographic variability. GAZULIS & CLARKE 2006 apply the concept to an abstract space representation mimicking the variable input of UGMr. It reflects a kind of digital petri dish with perfect simulation constraints. The artificial environment can be seen as a synthetic version of the regular grid UGMr input (cf. 4.3.2): an urban land use map, a slope layer, the transport network as well as an exclusion layer (Fig. 4.9). Here, the urban input is just a single urban cell in the middle of the image whereas all other cells are defined as non-urban. The slope has a minimum value of 0 % and increases concentric-radially to a maximum value which is equal to the maximum slope value to be found in the Ruhr (70 %). The transport network is represented by a single road crossing the center of the image from north to south. In this study, the exclusion layer is exchanged by the three total probability maps of urban growth of the Ruhr for the year 2025. For estimating the spatial impact of the scenarios, the particular probability map is allocated with a linear transition from high to low probabilities equivalent to their particular value range. In the south of the urban centre, the probabilities decrease from 1 to the particular medium value. This medium level continues northwards from the urban centre and decreases to zero. Thus, the maps are divided lengthwise from west to east.

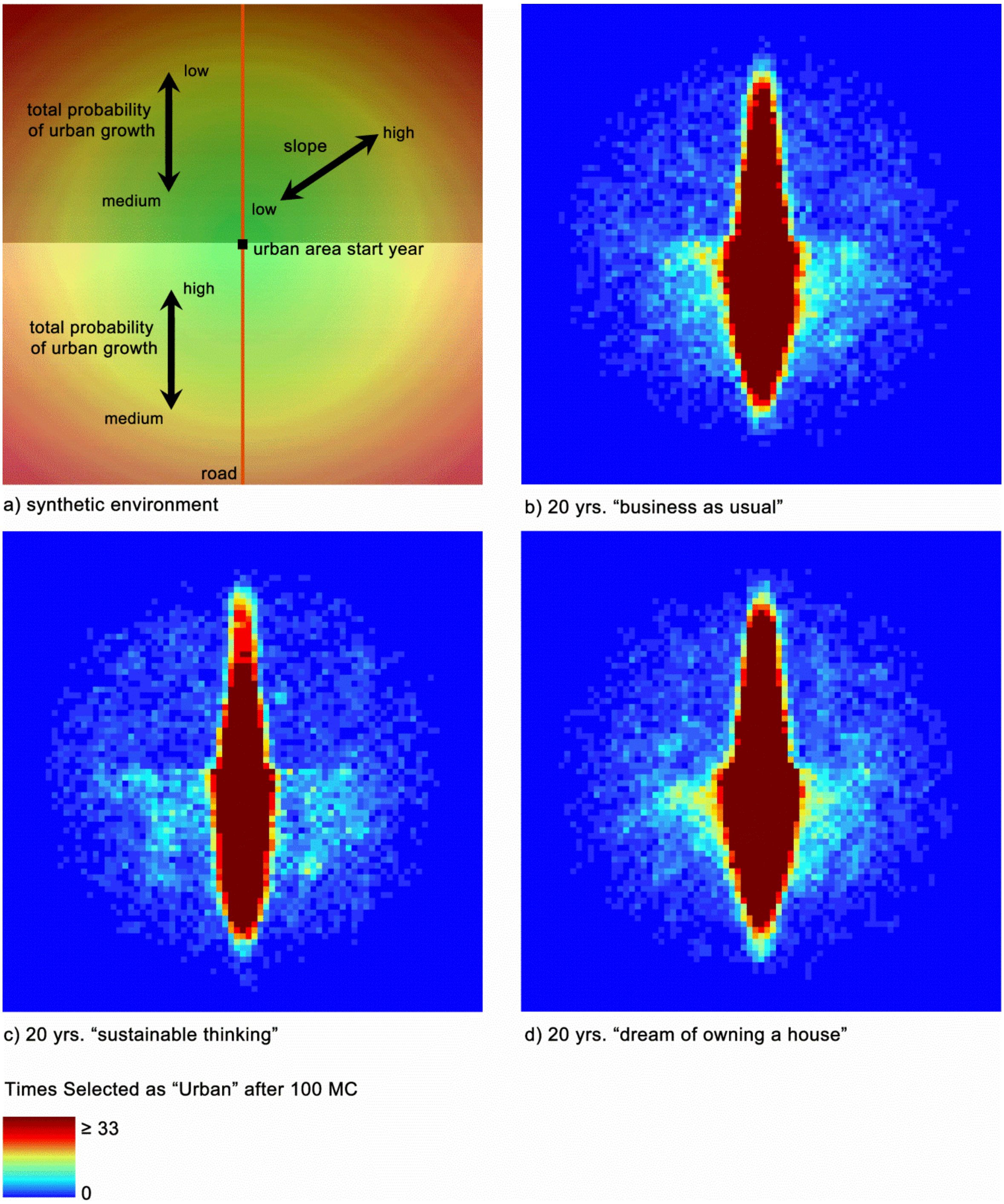

Figure 4.9. Urban simulation in a digital petri dish consisting of the fundamental elements of the Ruhr's urban area.

For every scenario UGMr-SVM is run with the calibrated growth coefficients (cf. 4.3.3 & 4.4.1) and 100 MC iterations. Hence, one can observe the allocation behavior of the CA under the MAS defined conditions of the Ruhr's urban areas. The border of high and medium probabilities of urban growth is distinct in all scenarios. The scenario "dream of owning a house" is the one where UGMr-SVM calculates and allocates the highest amount of urban growth. While the pattern is similar to the "business as usual" assumptions, it varies with "sustainable thinking". Here, the urban pattern is slim and less sprawled at the same time. All in all, the DNA of the Ruhr's urban areas reveals a tendency to edge growth and a high influence of the road network. Low probabilities cannot avoid the urban growth along the street in the northern part of the synthetic region. In contrast, they avoid a sprawled disperse pattern as can be found in the southern part.

4.5 Discussion and Conclusion

This study presents an integrated CA-MAS modeling approach to simulate the spatial pattern of urban growth in the declining polycentric Ruhr metropolitan area. Both AI strengths could be coupled: On the one hand, the ability to do *ad hoc* urban growth modeling, and on the other hand the simulation of individual decision making interacting on several organizational levels. By modeling from and to the pixel simultaneously, the CA-MAS approach captured the spatial pattern of urban growth as well as the processes of housing markets in shrinking urban areas. UGMr-SVM makes use of five growth coefficients and historic land-use information to model different growth types. In order to suppress its stochastic behavior, the CA was guided by adding an SVM probability map based on location-specific characteristics. ReHoSH simulates the behavior of stakeholders of real estate markets. Beside the migration of households, the price development as well as the conversion of potential residential areas on greenfield and brownfield sites can be analyzed by means of the MAS. By using the inter-comparable European Urban Atlas, the concept of semi-explicit urban weights could be developed. It served as a spatial canvas to transform the spatially-implicit MAS information of new housing constructions into the gridded environment of a CA. It enabled the simulation of different scenarios reflecting changes in the society as a whole. They illustrate what happens if the preferences for newly developed housing is increased or decreased by 5 % in two household groups. The total probability maps of "sustainable thinking" and "dream of owning a house" clearly influence the future rates of UGMr-SVM. Their spatial impacts are visualized with the concept of urban DNA and a digital petri dish. Hence, the generic growth elements of the Ruhr's urban area were uncovered.

Even though the proposed CA-MAS combination constitutes an innovative approach, it exhibits some limitations. Above all, UGMr-SVM is exclusively constructed for the modeling of spatial growth. The pattern dynamic of urban perforation (SIEDENTOP & FINA 2008) is not included and not simulated spatial explicitly. Having a closer look at the specific simulation conditions, the drawback is narrowed. While demolition is an important issue for city planning in the Ruhr, the phenomenon of urban perforation will not transmit a critical signal at the given study scale of 100 m (BBSR, 2012; HOSTERT, 2007; KROLL & HAASE 2010; SIEDENTOP & FINA, 2008). However, ReHoSh incorporates the demolition and vacancy rates influencing the quality of the supply in a community. Again, the quality determines among others the decision of households for a new dwelling in the particular community. Accordingly, a feedback loop between migration, vacancies, and price development is established so that the outcomes of shrinkage are taken into account in a spatially implicit manner. A second very important limitation is the focus on the housing market. Developments in industrial, retail or other urban uses are not directly included in ReHoSh. Instead, SVM are applied to a layer stack of factors driving the allocation of urban cells. Here, residential areas are not distinguished from other urban land uses so that they are indirectly included in the CA-MAS compound in total. Thirdly, ReHoSh assumes a constant household structure. The separation of our society or lifestyle changes is not captured. Hence, the shrinkage of households is equal to the shrinkage of the population.

In summary, the study presents a promising combination of AI techniques for investigating the patterns and processes as well as causes and effects of the developments of urban systems. Future very high resolution satellite systems with high repetition rates will deliver new spatial data sets and therefore improve the understanding of patterns and processes of urban growth. Further research should focus on the extension of ReHoSh. The inclusion of commercial land-use and transport systems as well as a splitting of the city agents into real estate managers and administrate members will enhance the plausibility of ReHoSh. Apart from the housing preferences, other parameters could be changed in order to implement more possible effects of a scenario. Additionally, it remains a challenging aspect to integrate and synchronize the different spatial and temporal scales of UGMr and ReHoSh. The presented coupling solution treats the agents' decisions on an aggregated temporal as well as spatial level. Both, the conversion of a pixel and the decision making of an agent are accomplished discretely after one year. Hence, an approximation to the everyday scale would be desirable. Finally, an important future pathway is a further incorporation of stakeholders and decision makers. Although the presented soft AI combination can be regarded as advantageous to communicate a visual sense of what an alternative future look like, the approach would gain if it allows users to enter rules or change the behavior of urban agents. That way, it would be possible to further investigate and uncover the behavior of complex urban systems re-acting to changing global conditions.

5 Summary and Outlook

"Cities are more than the people that inhabit them. There is a built environment that they influence and are shaped by. Therefore, interactions between urban infrastructure and mobile entities are necessary to represent real urban systems" (NARA & TORRENS, 2005: 6). In line with this statement, the present thesis aimed to geosimulate integratively the future urban sprawl in the Ruhr. By constructing a hybrid modeling approach based on the artificial intelligence simulation techniques of cellular automata and multi-agent systems, settlement-pattern dynamics and the regional housing market dynamics were to be captured and predicted. In doing so, the modified version of SLEUTH, UGMr, functioned as the CA component. It was coupled with an SVM-based probability map and implemented to a research transect of NRW. Thus, UGMr-SVM was applied in order to model the future urban sprawl of the Ruhr. Simultaneously, the recently developed MAS ReHoSh was applied in order to simulate the residential mobility and future price development of the housing market in the Ruhr area. For this purpose, morphological growth as well as processes and behavior alterations of a shrinking urban region were to be simulated. Finally, both AI strengths were integrated into one hybrid modeling approach and applied to model the patterns and processes of three different scenarios of changing housing preferences in the Ruhr.

In the introduction section of the thesis seven research questions were outlined and then answered successively in the subsequent chapters. In what follows below, the results and limitations of the applied modeling approach are to be presented before this study will conclude with an outlook delineating a perspective for further research.

5.1 Enhancement of the Cellular Automaton SLEUTH with Support Vector Machines

The main research goal of section 2 was to answer the question if the performance of the CA SLEUTH (UGMr) can be enhanced by using the machine learning algorithm of SVM (research question (Rq.) 1). This was to be achieved by adding an SVM-based probability map where geophysical and socioeconomic forces drove the local suitability of urban growth. For this purpose, the appropriateness of the SVM-based probability maps to allocate urban growth were assessed and compared to a standard BLR model (Rq. 1a & 1b). The ROC assessment clearly showed that the curve of the SVM model reached a stable level much earlier than the BLR curve which increased more linearly and stagnated only at high percentile groups. With an outstanding AUC value of 0.94 compared to a value of 0.76 the SVM-based probability map obviously outperformed the BLR model. Furthermore, the SVM approach assigned more values in the edge regions of probabilities of 0-33% and 67-100% and fewer values in between. Accordingly, the SVM-based probabilities exhibited a higher certainty compared to those derived by BLR.

The SVM- and BLR-based probability maps were combined with the exclusion layer of UGMr and applied to a transect of NRW. A third model was set up only containing the restricted area map without any probabilities. In order to assess the performance of the different UGMr versions and to validate the models, an accuracy assessment was applied in which the urban growth models were tested regarding their certainty (cut-off value) and their probability performance (ROC) in comparison with the randomness (Cohen's Kappa), the quantity ($\varkappa_{histo}$) and the allocation ability ($\varkappa_{loc}$) as well as the fuzziness of urban growth (MRV) (1c). The calibration and the validation of the model were separated carefully. Unlike the procedure in the calibration process where persisted urban areas were maintained, the ability of the model to simulate urban growth exclusively was assessed.

As a reliable result, it can be stated that the quantity and the allocation performance of SLEUTH-UGMr are augmented clearly when coupling it with a BLR- or SVM-based probability map. The Kappa results revealed that the integrated versions of UGMr, and especially UGMr-SVM, lift the overall prediction accuracy in comparison to a random distribution from a poor to a fair level. The fair Kappa value indicated that the model was not feasible for a perfect local prediction with a spatial resolution of 100 m. Here, the MRV allows a certain tolerance range regarding the predictive efficiency of location and takes the quantity performance into account as well. The null resolution was already achieved at a resolution level of one. While the MRV values of the three UGMr versions showed only slight differences, the curve of agreement over different resolutions signaled that the integrated UGMr models are characterized by a more robust performance.

Even though UGMr-SVM also exhibited the best ROC value, the certainty of the SVM-based probability map could not be transferred directly into the CA. The stochastic variability of UGMr-BLR regarding the emergence of urban cells could be depressed, but it performed nearly as reliably as UGMr-SVM. Though distinctly more stable than the "unguided" UGMr, the stochastic variability was still very high. A careful cut-off value selection is thus highly recommended.

The analyses of various geophysical and socioeconomic forces driving the local suitability of urbanization constitutes a further advantage of the integration of a probability map into SLEUTH-UGMr.

5.2 Driving Factors of Urban Growth in North Rhine Westphalia and the Ruhr

Residential land uses claim 12 % of the region's area occupying the biggest amount of the region's built-up area (Regionalverband Ruhr, 2011). The simulation of future urban growth in the Ruhr performed in the thesis used ReHoSh to address housing construction as one proximate driving factor as well as household migration, real estate trade, and planning directives as underlying driving factors of urban sprawl. However, for a holistic view of the future further underlying driving factors as well as settlement uses such as traffic or commercial and industrial ones must be taken into consideration. The spatially explicit part of the constructed hybrid modeling approach, the CA UGMr, does not distinguish between different urban land uses but incorporates every settlement and traffic area exhibiting a high degree of impervious surfaces. In contrast, UGMr allows no insights into the causes and processes of urban growth. The use of an SVM model furthermore allowed an attempt at answering research question 2: “which driving factors influence the physical urban growth in NRW in general and in the Ruhr in particular and how do they take effect”?

SVM were applied to a raster layer stack consisting of different geophysical, socioeconomic as well as demographic driving factors of urban growth. A forward feature selection was carried out and the effect rank of the variables in the SVM model was analyzed for both regions dealt with in the study: the west-to-east transect of NRW and the Ruhr. The first variable depicted in the selection for the transect of NRW was the distance variable “DistRiver”. Together with “DistAirport” it probably indicated the Rhine agglomeration of Cologne and Düsseldorf. Among the distance measurements according to von Thünen, the driving factors of the labor market (“JobsSec” and “JobsTert”) and the living conditions (“NetDewllArea”) achieved the best results. The weight of the distance to the river may reflect its importance for the past settlement nuclei and its function as an international trade way. In contrast, the distance to the next railway station served as the most important feature in the SVM model applied to the Ruhr. It is another link to the past of NRW where a freight transport network traversed the industrial and mining region. Again, it can be stated that the characteristic attributes of the distance-related variables and the number of jobs are more suitable for constructing the SVM model than other socioeconomic or demographic variables.

It must be remembered that SVM models allow absolutely no insight into the effect direction of their features. Due to the main research question of section 2, the SVM model of the transect of NRW has been compared with a BLR model. Therefore, the effect direction of the variables could additionally be assessed for the transect of NRW. It is only valid for the BLR model and its specific allocation characteristics. Here, every variable indicating the occurrence of settlements in the base year 1984 consequently has a negative influence on the probability of urban growth: At the same time there is a positive relation between the migration pattern for the age group 25 to 50 years and urban growth. New settlements seem to be developed predominantly in the suburban and rural regions of the study area and thus in areas with a relatively lower population and job density.

5.3 The Future of Urban Sprawl in the Ruhr – Allocation and Quantity

After the allocation and quantity performance of the CA SLEUTH had been enhanced, UGM-SVM was implemented to model the future urban sprawl of the Ruhr so that the third research question “where and at what rates will future land consumption in the Ruhr take place?” (Rq. 3) could be answered in section 3. In this context, the validation indices for UGMr-SVM showed (very) good values around 0.8 (ROC and Kappa) and 0.93 (MRV).

A “business as usual” scenario was assumed for the simulation run from the year 2005 to 2025. The cut-off value for transforming the map after 100 MC iterations into a binary land-use map was chosen at a level where the best balance between location and quantification performance could be reached (33%). In total, UGMr-SVM predicted and distributed an urban growth of 3,995 ha, which is ~3 % of the urban area observed in 2005. It was detected that the allocation of urban cells with UGMr-SVM is strongly tailored to already existing urban areas. The dominant predicted growth type was the external growth, which simultaneously closes gaps in the existing settlement areas of the Ruhr. While the "spread" coefficient was the main growth impetus in the simulation, the dispersive growth and the emergence of new settlements ("breed") were of minor importance. Hence, UGMr-SVM captured the "metropolitan suburban sprawl" type with high values of new land consumption in the core areas (SIEDENTOP & FINA, 2010). Of course, the MC iterations and the combination with SVM suppressed the UGMr's preference for a stochastic allocation of urban cells. The simulation of a sprawl in the rather rural hinterland thus could not be simulated with absolute certainty. Nevertheless, the aim of the German federal government claiming a reduction of land consumption to 30 ha per day until 2030 seems to be unlikely.

5.4 The Future of the Housing Market of the Ruhr – Households and Prices

The image of the Ruhr as a growing conurbation exhibiting a permanently extending morphology has to be refuted if you shift the focus from its physiognomy to societal change and economic wealth. In this context, the Ruhr is a declining region following the same pathway as other members of the "rusty fellowship". Accordingly, the region is struggling with archetypical problems of former mono-functional manufacturing cities depending on mining and heavy engineering. As UGMr-SVM is a pure growth model unable to simulate behavioral processes of actors of the Ruhr's housing market, the agents came into play. An MAS was implemented in order to answer the question "where will households migrate and how will housing prices develop in the Ruhr?" (Rq. 4).

ReHoSh comprises not only household preferences but also the development of potential dwelling areas as well as housing prices and housing supply. Since ReHoSh was developed only recently, it became one aim of this thesis to calibrate and validate the performance of the MAS. As the data base of RuhrFIS delivered the input data used in the calibration, a way had to be found to use surrogate validation data. Here, a synthetic data set was created involving, among other things, potential dwelling areas and real estate prices. For testing the generalization of ReHoSh, the four districts of the Ruhr were neglected during the calibration run whereas they had initially been added to the cities in the validation phases.

The simulation of regional household migration trends with ReHoSh achieved deviations under 10 % for all communities while ten communities even showed deviations under 5 %. Notably, two-thirds of the communities in the group of the smaller-sized households still depicted this accuracy level. This was the group showing the highest oscillation so one can state that ReHoSh is able to reflect behavioral attitudes of different household types in regions facing urban decline.

ReHoSh simulates the household development by establishing an interaction between the household agents and the stakeholders of the housing market driving the housing-related factors like demolition rates or the raise of new dwelling supply. Addressing economy theories like the equilibrium price, the price elasticity, and the "hog cycle", land values and real-estate prices could be simulated in dependence of the individual residential behavior alteration. The results showed that land values and real-estate prices deviate less than 10 % in nearly all of the modeled cities and districts. Except for one outlier, all municipal land values could be captured with a deviation below 5 %.

After ReHoSh had been validated, the MAS was set up for a "business as usual" scenario. The average of 1,000 simulation runs served as results for the development of the Ruhr's housing market until the year 2025. A trend of local land values could be observed reflecting an overestimation of housing supply by ReHoSh at the beginning of the simulation and leading to a significant and immediate price decrease. Besides, ReHoSh modeled distinct municipal differences: Gelsenkirchen and Recklinghausen are the only cities and districts in the simulation displaying demographical growth. In contrast, Duisburg and Hagen served as examples of a clear demographic decline. The high housing supply in the extra-urban regions in combination with a moderate price level was found to be raising the attraction of peripheral communities for the young, small households leading to a probable overestimation of this household size type.

5.5 Loose Coupling of Pixels and People – SLEUTH meets ReHoSh

The results of ReHoSh are spatially implicit and aggregated on the community level. For a further spatially explicit analysis of ReHoSh and in order to visualize the development of the regional housing market against the backdrop of the morphological urban sprawl simulated by UGMr-SVM, simple spatial joins were used to couple both AI results loosely (Rq. 5).

Two difference maps were produced to answer the questions of "how will future household densities in the Ruhr look like" (Rq. 5a) and "what are the differences in the spatial distribution between household groups regarding their age and size?" (Rq. 5b). In general, the household type older than 45 years and 1-2 persons is by far the largest group in every community. The biggest differences for densities between younger and older households could be found in the rather rural districts Wesel, Hagen and Ennepe-Ruhr as well as in the peripheral city of Hamm. Here, the group of younger households is significantly smaller than that of the older ones. Virtually the same holds true for Herne. The city borders on those communities showing difference values below the average, which reflects the relation between the potential of dwelling place, price development, and the varying demand of different household groups established by ReHoSh. A low potential of dwelling places led to higher prices which in turn led to a lower demand of young households.

The second difference map contrasted smaller households with 1-2 persons and households with 3 and more persons. Interestingly, this difference map could almost be regarded as a complement to the other map: The core cities of Dortmund, Bochum, Gelsenkirchen and Essen depicted the largest differences between the two household size types. Moreover, the spatial pattern reflected the preference of the larger households, for instance families, for rural areas in the hinterland.

The third question of section 3 "how will the development of prices for existent properties and newly developed housing differ regionally?" (Rq. 5c) could be answered by means of a spatial join of pixels and prices. A homogenous price distribution within a city or a district was assumed when a price difference map 2005-2025 depicting negative and positive trends was created. Thus, one could compare the development of real-estate prices and land values within the different communities of the Ruhr. In doing so, three groups were depicted. In the first group, the price development of land and properties proceeded similarly with a price decrease (Bochum, Duisburg, and Hagen) or an increase (Hamm, Gelsenkirchen, and Ennepe-Ruhr) of both residential types. The second group consisted of the three districts Recklinghausen, Unna, and Wesel with very high increases in real-estate prices and very high decreases in land values. The last group comprised the other cities located in the southwestern and south-central part of the Ruhr. They showed increasing land values and decreasing real-estate prices. As a result, urban core areas are less frequently demanded while a slight migration trend towards the suburban regions can be assessed.

5.6 Semi-explicit Urban Weights – A Concept for Strong Coupling of Cells and Agents

The main technical challenge of this thesis was to couple the geosimulation techniques of CA and MAS into one integrated hybrid modeling approach. In doing so, the settlement-pattern dynamics and the regional housing market dynamics can be assessed at the same time. Hence, a concept needed to be developed "in order to transfer the outcomes of individual decision making of interregional housing markets into a cellular environment" (Rq. 6). The implementation of SVM already reduced the drawback of UGMr regarding the "black-box"-like calculation of urban growth rates. What is more, the machine learning algorithm guided the CA by including location-specific characteristics. But still, the growth coefficients of UGMr-SVM determined the quantity of new urban cells to be allocated with every growth step. Additionally, a relation to dynamic state changes in the coupled human-environment was not incorporated in UGMr-SVM. Hence, the processes of the housing market of the Ruhr which are driven by the behavior alteration of its stakeholders were not included. The quantity of potential new dwellings is dependent of individual decision making beyond the discrete dimension of a pixel. Accordingly, the valorization of potential dwelling areas calculated by ReHoSh needed to be transmitted into UGMr-SVM: cells should be coupled with agents.

The concept of semi-explicit urban weights was introduced in section 5 to turn the spatially implicit information of ReHoSh into a spatially explicit advice acting as a demand guideline for UGMr. It was supposed to mitigate between the poles of demand and supply, pattern and process, society and space, as well as pixels and people. Semi-explicit urban weights were defined as the simulated dwelling supply varying on community level assigned to cells being in line as potential dwelling areas. Thus, the probability of new housing constructions was disaggregated from the community level and scaled up to area units containing selected land-uses. ReHoSh simulated the local housing preferences and the future construction rates of residential land uses. The modeled supply of dwelling areas was divided by the potential dwelling areas of 2010. Subsequently, these potential dwelling areas were assigned to selected land-use classes representing potential dwelling areas of the inter-comparable European Urban Atlas. As a result, one received a map reflecting the semi-explicit urban weights. They finally enabled the implementation of three scenarios dealing with the change of individual housing preferences (Rq. 7).

5.7 "Sustainable Thinking" or "Dream of Owning a House" – Implementation of Urban Sprawl Scenarios in SLEUTH and ReHoSh

The integrated hybrid CA-MAS model was set up to geosimulate different scenarios of the future urban sprawl in the Ruhr addressing patterns and processes at once. The scenarios followed four criteria defined by relevance, credibility, legitimacy, and creativity. They should reveal major trends in the political and economic framework constraints influencing individual behavior alterations. Beside a "business as usual"-scenario, two simple scenarios were outlined: "sustainable thinking" and "dream of owning a house". "Sustainable thinking" captured the "30 ha goal" of daily land consumption and assumed that people try to implement the sustainable handling of the limited resource land. The other scenario "dream of owning a house" reflected the steady wish of families to own a house in sub- and exurban areas and dealt with the development of new settlement areas consisting of semi-detached buildings as one of the key drivers of urban sprawl in Germany.

The household preferences of ReHoSh acted as the set screws to answer the questions of "which quantitative and regional differences arise in the context of different dwelling types" (Rq. 7a) and "how will the spatial dynamics of urban sprawl change dependent on behavior alteration by private and public stakeholders" (Rq. 7b). The preferences for existent dwellings in the group of family-reflecting households as well as in the biggest group (1-2 pers, > 45 yrs.) were increased by +5 % for "sustainable thinking" and decreased by -5 % in "dream of owning a house". All other parameter settings of ReHoSh were maintained. The slight differences in the housing preferences led to partially strong variations in the resulting construction rates of new built-up areas with residential uses. Essen and Gelsenkirchen, for instance, were simulated to convert most of their potential dwelling areas already in the "business as usual"-scenario. This contrasted sharply with the "sustainable thinking"-scenario. Nearly all cities exclusively converted their potential dwelling areas in the scenario "dream of owning a house".

The scenario results were transferred to the maps of semi-explicit urban weights and introduced into UGMr-SVM for a simulation of urban sprawl until 2025. In 2005, the urban areas of the Ruhr had an extent of 132,012 ha. In the "business as usual"-scenario, they increased to 136,007 ha in 2025. The "sustainable thinking"-scenario reduced the growth rate from 2,273 ha to an extent of 134,285 ha. In contrast, the "dream of owning a house" evokes a rate of 8,129 ha and an extent of 140,141 ha. Merely a few cells were just simulated as "urban" in one single scenario. Higher growth rates even led to a more extensive urban land conversion in rather remote areas.

The spatial impacts were visualized with the concept of urban DNA and a digital petri dish. It is an idealized environment manifested as a grid image and consists of one urban cell, a concentric slope, one single linear road as well as the scenario probabilities. The probabilities built a linear transition which was divided lengthwise from west to east. Hence, the digital petri dish of an urban region uncovered the generic growth elements – similar to DNA – of the Ruhr. In doing so, research question 7c, namely "what spatial differences emerge in an abstract environment with perfect constraints and fundamental urban structure elements", could be answered. After 100 MC iterations during 20 years of urban sprawl, one was eventually able to observe the behavior of the urban CA under the MAS-defined conditions of the Ruhr's urban area. It revealed a tendency to edge growth and a high influence on the road network. Even low probabilities could not avoid the urban growth along the streets in the northern part of the synthetic region. In contrast, they avoided a sprawled disperse pattern as can be found in the southern part.

All in all, the integrated hybrid model of UGMr-SVM & ReHoSh combined the artificial intelligence of CA and MAS. Three different scenario assumptions could be captured. They formulated varying conditions, constraints, and driving factors of the macro-level influencing the micro-level behavior of the decision makers and stakeholders of the housing market of the Ruhr. The results are different supplies of new dwellings and thus spatial patterns and intensities of urban sprawl.

5.8 What's next? From Hybrid AI Prediction to Spatial Decision Support

In the course of this thesis and for the first time ever the CA SLEUTH was enhanced by using SVM. The MAS ReHoSh was calibrated and validated, and firstly integrated with SLEUTH into one hybrid modeling approach by applying the new concept of semi-explicit urban weights. So far, this is the only study coupling the AI techniques of CA and MAS to model urban growth of a polycentric German region *ad hoc* and to simulate individual decision making interacting on several organizational levels. UGMr is able to simulate emergence phenomena of urban patterns; SVM introduces driving factors of urban growth into the CA; ReHoSh again considers the supply-oriented factors of communities and housing demand due to the behavior alteration of the residents. Altogether, they address the complexity characteristics of urban systems in a reliable, valid, and reality-oriented manner.

Even though it was not the aim of this study to develop the "ideal" integrated model of urban land-use change, one can still compare the CA-MAS approach established in the thesis with the requirements listed in the introduction section (cf. Sect. 1.2.5). It can be seen that most of them are met while others are not. Accordingly, UGMr-SVM & ReHoSh incorporate a variety of physical elements, actors, processes and the housing market as one basic organizing principle of urban systems as well as interactions and feedbacks between multiple organizational levels of hierarchy. Moreover, the model combination simulates urban growth under conditions of demographic decline and economic shrinkage.

In contrast, the requirements that have not been met offer a perspective for future research within the field of hybrid geosimulation of complex urban systems in Germany. For example, an interaction with the transportation system has not been provided in a detailed manner. Indeed, the street network is part of the modeling procedure of SLEUTH and is addressed indirectly via the cost-weighted distance-related variables of the SVM model. Here, the interpretation of the driving factors is of course limited due to the disaggregation methods of the variables and should better be treated as location-specific characteristics. Again, it must be noted that the implemented CA is a sheer urban growth model. The phenomenon of urban perforation is not included yet it needs to be if the developed hybrid model approach should be applied for long-term analyses beyond the temporal dimension of this thesis. Another very important limitation is the focus on the housing market: Developments in industrial, retail or other urban uses are not directly included in ReHoSh. The same holds true for the inclusion of different socioeconomic statuses or lifestyles of the household agents in the MAS. Thus, the real-world housing preferences of residents would be simulated in a more sufficient and plausible manner. Finally, UGMr-SVM does not distinguish between different urban land uses but only between urban and non-urban areas based on their fraction of impervious surfaces. Future satellite systems may improve the base data input for spatially explicit urban growth modeling in terms of spatial, temporal, and semiotic resolution.

It can be concluded that all research questions could be answered successfully. By modeling from and to the pixel simultaneously, the CA-MAS approach captured the spatial pattern of urban growth as well as the processes of housing markets in shrinking urban areas. The results derived by the coupled power of both AI techniques may serve as valuable spatial decision support since they can be applied to the calculation of important key indices of urban sprawl in the shrinking region of the Ruhr: urban density, change in urban density, new urban area consumption, and the number of new dwellings in newly developed urban areas (SIEDENTOP & FINA, 2008). The integrated hybrid model of UGMr-SVM can be easily applied as well as comprehended in practice in terms of financial and human resources (HAASE et al., 2012). The relatively coarse resolution of 100 m makes the UGMr-SVM & ReHoSh and its results still a fruitful contribution to the state development plan (BREUER & JÜRGENS, 2001). The used modeling platforms of XULU and Repast are both written in the object-oriented programming language Java and are open-source licensed. Hence, this does not only facilitate a stronger coupling and integration of the models but also guarantees an introduction to the scientific community. This helps overcome the bottleneck of scientific computing (WILSON, 2006).

Against the backdrop of global change including a rapid and unprecedented urbanization in the developing countries, the availability of evaluative tools appears to be central. The pressure on our world resources increases daily so science and practice must intertwine more and more in order to direct the future development of the society, the economy, and the environment into sustainable channels. We do not model to predict the future but to change it!

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