SPRAWLING CITIES AND SHRINKING REGIONS – FORECASTING URBAN GROWTH IN THE RUHR FOR 2025 BY COUPLING CELLS AND AGENTS

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With 9 figures and 7 tables
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Summary: 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".

Zusammenfassung: 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. Nach neueren Erkenntnissen geht die Flächeninanspruchnahme zwar zurück, doch ist die Erreichung des 30-Hektar-Ziels nach wie vor in weiter Ferne. Gerade auch in schrumpfenden Regionen ist eine ungebremste Ausweitung von Siedlungs- und Verkehrsflächen zu beobachten. Die Gründe für diese Entwicklung lassen sich unter anderem in der angebotsseitigen Bereitstellung von Wohn- und Gewerbeflächen im Zuge einer wachsenden interkommunalen Konkurrenz suchen. Die Landnutzungsmodellierung beider Großtrends kann Aufschlüsse über Prozesse, Ursachen und Folgen der Flächeninanspruchnahme im sozialen wie ökologischen Bereich geben. Zu diesen Techniken gehören auch Modelle der Künstlichen Intelligenz (KI) wie Zelluläre Automaten (CA) und Multi-Agenten Systeme (MAS). Während sich CA mit der Entwicklung von diskreten räumlichen Einheiten beschäftigen, simulieren MAS Verhaltensänderungen von Entscheidungsträgern. Die vorliegende Studie stellt einen Ansatz zur Integration der beiden komplementären KI-Techniken vor und kombiniert das MAS ReHoSh (Residential Mobility and the Housing Market of Shrinking City Systems) mit dem urbanen CA SLEUTH. Dieser ist einer der am besten untersuchten räumlich-expliziten Landnutzungsmodelle und wurde bereits in zahlreichen Regionen der Erde angewendet. Zur Verbesserung seiner Allokationsfähigkeiten wird SLEUTH hier durch den Einsatz von Support Vector Machines „geleitet“. Bei ReHoSh handelt es sich dagegen um ein junges MAS, das entwickelt wurde, um lokale Wohnungsmärkte in schrumpfenden Stadtregionen zu simulieren. Städte und Haushalte formen die proaktiven, mobilen Entitäten des Modells, die über Wanderungen, zyklische Preisanpassungen und Bereitstellung von Wohnraum miteinander interagieren. Die Untersuchung führt das Konzept von semi-expliziten urbanen Gewichtungskarten ein, um den durch individuelle Entscheidungsfindungen errechneten Bedarf von Neubauten zu de-aggregieren und in eine zelluläre Umgebung zu transferieren. Der CA-MAS Modellverbund wird kalibriert und zur Prognose der städtischen Zukunft des Ruhrgebietes angewendet. Neben einem "business as usual" werden zwei weitere Szenarien für das Jahr 2025 implementiert, die die Veränderung von Haushaltspräferenzen bei der Wohnstandortsuche unter

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gesamtgesellschaftlichen Dynamiken repräsentieren sollen: zum einen die Verbreitung einer nachhaltigen Denkweise bei den privaten und öffentlichen Entscheidungsträgern, zum anderen der stetige Wunsch nach einem Eigenheim und dem „Wohnen im Grünen" in sub- und exurbanen Räumen. Die erzeugten Wahrscheinlichkeitskarten beeinflussen die Wachstumsraten von SLEUTH eindeutig. Die Szenarien konnten erfolgreich an den CA weitergegeben und unterschiedliche Ausdehnungen der Siedlungsfläche des Ruhrgebietes für das Jahr 2025 simuliert werden: 136.007 ha ("business as usual"), 134.285 ha ("sustainable thinking"), und 140.141 ha ("dream of owning a house"). Abschließend werden die räumlichen Effekte dieser Szenarien anhand des Konzeptes urbaner DNA analysiert. Es wird deutlich, dass ein Fortschreiten von urban sprawl nur mit einem Szenario erreicht wurde: "sustainable thinking".

Keywords: Multi-Agent Systems, Ruhr area, SLEUTH, Support Vector Machines, urban decline, urban growth

1 Introduction

During the 20th century, the environment of Central Europe was shaped by extensive growth of urban areas, leading to sprawling urban agglomerations. Morphological growth of cities is still ongoing in Central Europe, but currently a second major trend is superimposed on this process: urban decline. Administrations are confronted with aging populations, demographic shrinkage, a loss of economic capacity, as well as ever-increasing land consumption (Couch et al. 2005; Haase et al. 2012; Kabisch et al. 2006; Schwarz et al. 2010; Siedentop and Fina 2008). The modeling of both growth and decline 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 been incorporated into land-system simulations to address the complex challenges of transitions in urban areas as open, dynamic systems (Alcamo et al. 2006; Batty 2005; Benenson and Torrens 2004; Verburg et al. 2004a). Among those AI techniques are cellular automata (CA) and multi-agent systems (MAS) (Batty 2005; Benenson and Torrens 2004; Silva and 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 related to each other through communication and actions rather than through fixed spatial links (Benenson and Torrens 2004; Koch and Mandl 2003; Nara and Torrens 2005; Rauh et al. 2012; Silva and Wu 2012; Parker et al. 2003; 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 and Toetzer 2003). CA, however, are one of the most popular AI simulation tools. This is mainly due to their relative handling ease combined with their ability to simultaneously identify complex pattern developments. 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 time step (5) (Barredo et al. 2003; Batty and Xie 1997; Clarke et al. 1997; Hilferink and Rietveld 1999; Landis 2001; Tobler 1979; White and Engelen 1993; Wu and 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, the integration of CA and MAS systems promises to fulfill "…the need for hybrid systems," identified by Wu and Silva (2010, 253) as a leading challenge in land-system science, also thereby linking pixels with people (Geoghegan et al. 1998; Lesschen et al. 2005; Rindfuss and Stern 1998; Silva 2011; Verburg et al. 2004b; Wood and Skole 1998). Studies directed at coupling CA and MAS often focus on specific urban-change phenomena, including:

- Gentrification and segregation (Benenson et al. 2005; Nara and Torrens 2005);
- Suburbanization (Loibl and Toetzer 2003);
- Rural-settlement development (Liu et al. 2013);
- Transport systems (Beckmann et al. 2007);
- Spatial planning (Ligtenberg et al. 2001);
- 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 and 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 1 depicts the workflow for this study. The CA implemented here is a modified version of the SLEUTH Urban Growth Model (UGMr–depicted in the red box in figure 1) (Clarke et al. 1997; Goetzke 2012). SLEUTH has been applied in numerous urban-growth studies throughout the world (Clarke et al. 1997; Goetzke 2012; Rafiee et al. 2009; Silva and Clarke 2005; Wu et al. 2008), and stands as one of the most thoroughly assessed urban CA (Chaudhuri and Clarke 2013). 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–shown in blue, above) (Cortes and Vapnik 1995). The MAS compartment of the coupling framework is represented by ReHoSh (in green in figure 1). ReHoSh captures the interactions between housing market stakeholders and the development of potential residential areas in a declining urban environment (Rienow and Stenger 2014). The concept of semi-explicit urban weights is introduced and implemented to transmit ReHoSh results to SLEUTH UGMr. For this purpose, the semi-explicit urban weights are combined with the SVM-based probability map of urban growth (shown in buff above). Scenarios are developed which are

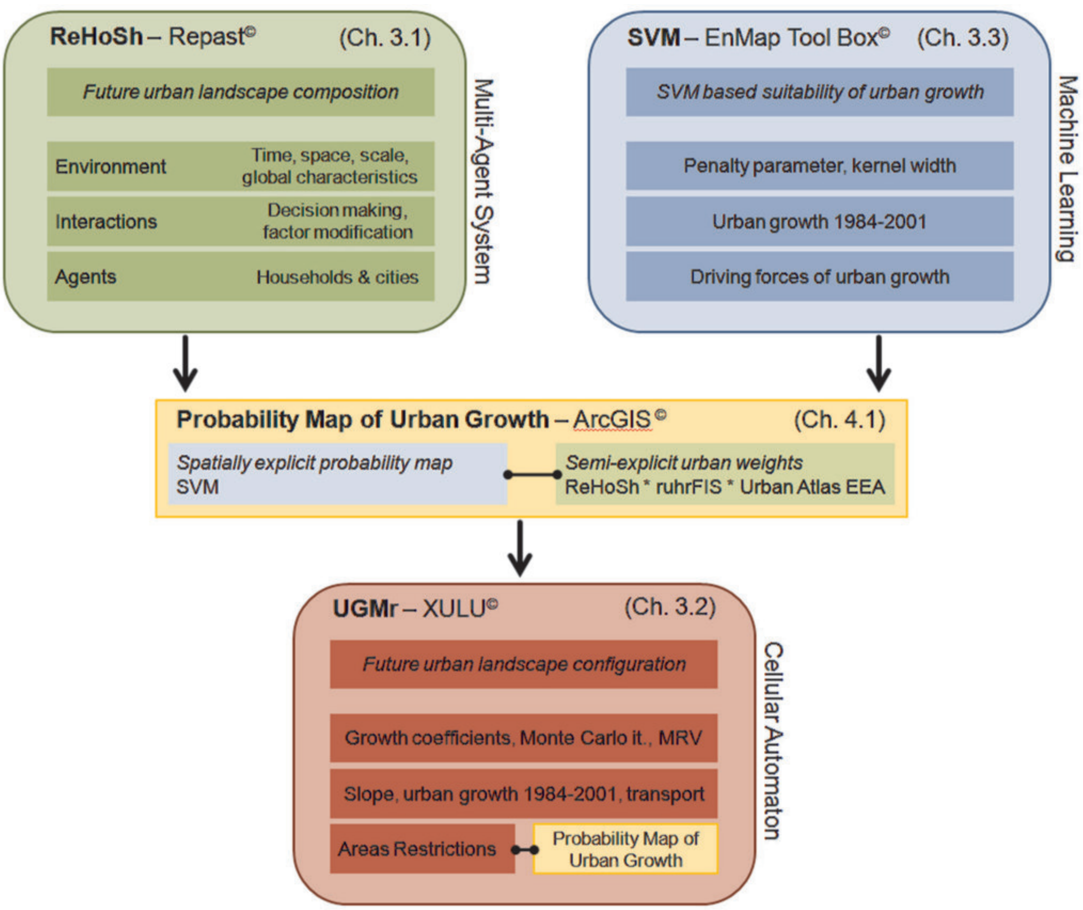

Fig. 1: Framework for coupling SLEUTH UGMr (CA) and ReHoSh (MAS) including the software and parameters used in the study

meant to illuminate future land conversion in the Ruhr within the context of changing housing preferences. These scenarios illustrate two possible future trends for the 2025 horizon: the dissemination of sustainable thinking among stakeholders, and the continuing desire by individuals to own a home in a suburban or exurban area.

Modeling results are subsequently analyzed by means of the concept of urban DNA (cf. Sect. 4.3).

The research directives of this study may be summarized as:

1. The development and formalization of a concept transferring individual decision making into the cellular context.
2. The implementation of an integrated CA/MAS focused on conditions of urban growth and contraction in the Ruhr.
3. The application of the coupled CA-MAS model to characterize the future of the Ruhr region for the year 2025, envisioning three separate growth/contraction scenarios.

The paper is structured as follows: Section 2 introduces the Ruhr research area and the applied data. The following Section 3 explains the implementation of the ReHoSh and SLEUTH models as well as the SVM application. Section 4 presents the concept and the approach for coupling the AI models and also includes our analyses of the results of three future scenarios for the region. The advantages and limitations of linking pixels and people in urban system modeling are discussed critically in Section 5, which also provides a short conclusion as well as an outlook for future research.

2 Study area and data

2.1 The Ruhr–urban growth meets urban shrinkage

The Ruhr lies in North Rhine-Westphalia in the western part of Germany (Fig. 2). The region is named after the Ruhr River, an important right-bank tributary of the lower Rhine. The Ruhr region extends from the Lower Rhine basin in the west to the Westphalian Plain in the north and the Rhenish Massif in the south. Within the Ruhr, 15 cities form the largest urban agglomeration in Germany, including a population density of 1,150 persons/km^2. In descending order of population, the largest Ruhr cities are Dortmund, Essen, Duisburg and Bochum; with populations between 370,000 and 580,000 (REGIONALVERBAND RUHR 2011).

Currently, the Ruhr region confronts a suite of socioeconomic problems common to all members of the ‘rusty’ fellowship in Europe (Couch et al. 2005): a demographic decline, an aging population, high unemployment rates, an incipient “brain drain” and a lack of incentives to attract prosperous ‘new economy’ service sector companies (ibid.). The overall regional population decreased from 5.4 to 5.1 million between 1996 and 2010. Ten percent of workers are unemployed and the numbers of employees in the service sector has been stagnant at 72% for the past twelve years. The Ruhr, therefore, may 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).

These negative characteristics contrast with the physical extension of the Ruhr’s cities. Between 1975 and 2005, the Ruhr urban agglomeration expanded in area by approximately 37,022 ha, with a total urban area increase from 94,990 ha to 132,012 ha. The region’s physiognomic pattern is dispersed, with populations concentrated on the urban fringes and exurban areas as well as in small and midsize towns in the cities’ functional field of gravity (Hommel 1984; Siedentop 2006). There are several causes for the demographic decline, including the trend towards smaller family households, the fiscal competition between communities, planning practices (greenfield instead of brownfield development), and the preference for low-density housing (Hirschle and Schürt 2008; Mielke and Münter 2008; Siedentop and Fina 2008). The question of how the ongoing demographic and employment contraction will affect the future urban pattern of the Ruhr is complex and complicated by structural transformations. The spatial pattern of “urban perforation” observed in Eastern Germany, where extensive demolition has taken place in center city areas, has not yet occurred in the Ruhr region. However, a parallel process of spatial sprawl and contraction in the region cannot be excluded for the near future (Schwarz et al. 2010; Siedentop and Fina 2008; Wiechmann and Pallagst 2012).

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 was provided by the monitoring project NRWPro. NRWPro is sponsored by the Ministry for Climate Protection,

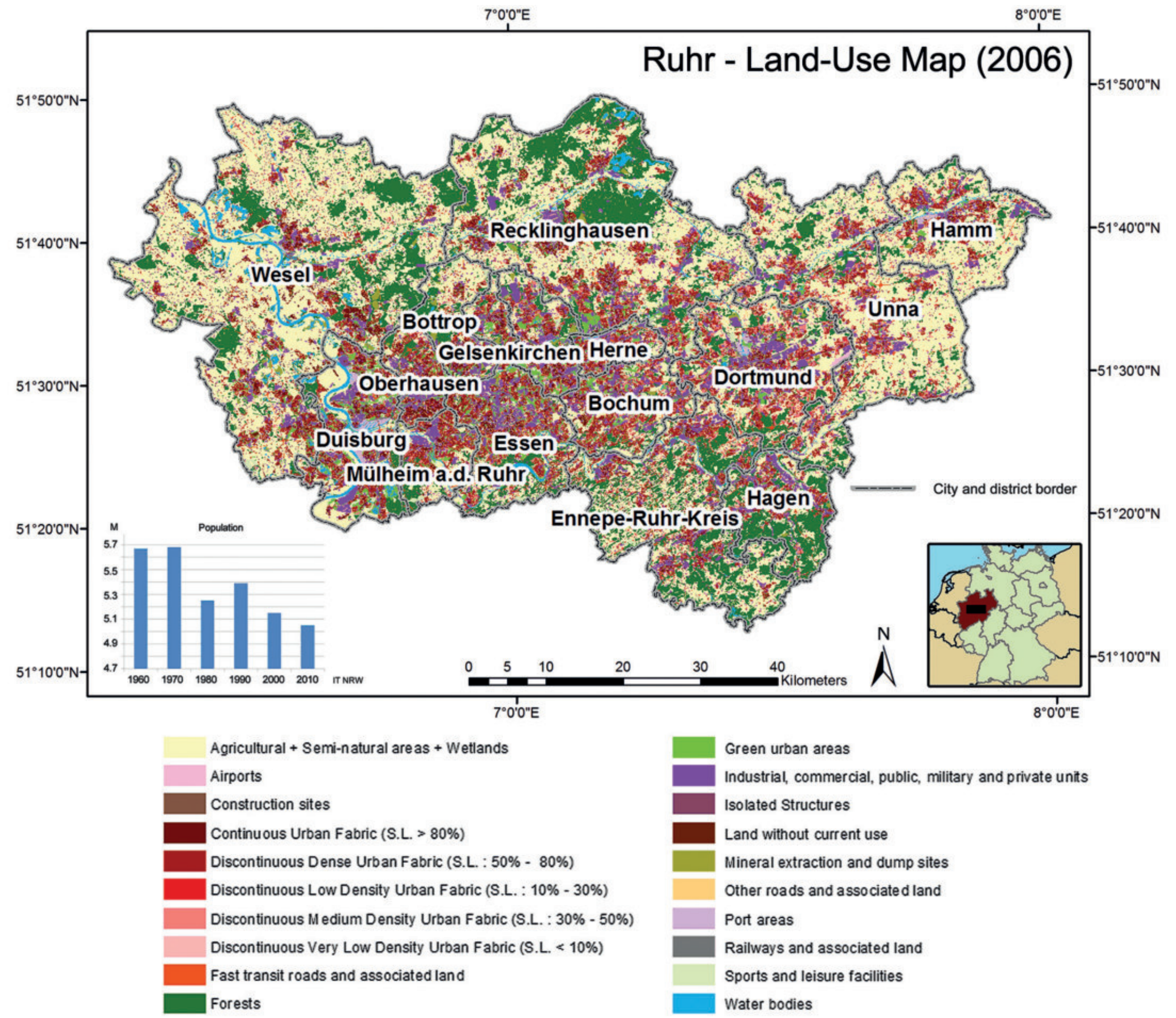

Fig. 2: 2006 Land-use map showing principal cities and districts of the Ruhr region in North Rhine-Westphalia, Germany (EEA)

Environment, Agriculture, Nature Conservation and Consumer Protection of the State of North Rhine-Westphalia. The data sets were classified using a hybrid approach of supervised classification algorithms and knowledge-based decision trees. The resultant classification simply identifies "urban" and "non-urban" areas, where an "urban" area is defined as having a surface imperviousness of a minimum of 25%. A validation analysis of the classification documented an accuracy of > 85%. In order to balance the spatial resolution and the spatial extent of the Ruhr, a grid resolution of 100 m was used. This classification procedure is described in detail by Goetzke et al. (2006) and Schoettker (2003).

For the calibration of SLEUTH, the 1984 data comprises the base year and the 2001 data constitutes the reference year. For the validation of SLEUTH, the 1975 data serves as the base year and the 2005 data is the reference year. Finally, the urban growth detected in the classified LANDSAT data between 1984 and 2001 is used to train the SVM model (Fig. 3).

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 entire Ruhr region (REGIONALVERBAND RUHR 2011). Actual land values and real estate prices are obtained from the information system of the NRW Expert Committee for Land Values (BORISplus.NRW 2012). The remaining parameter inputs (shown in Tab. 3) are derived from the State Office of Statistics (IT NRW 2013).

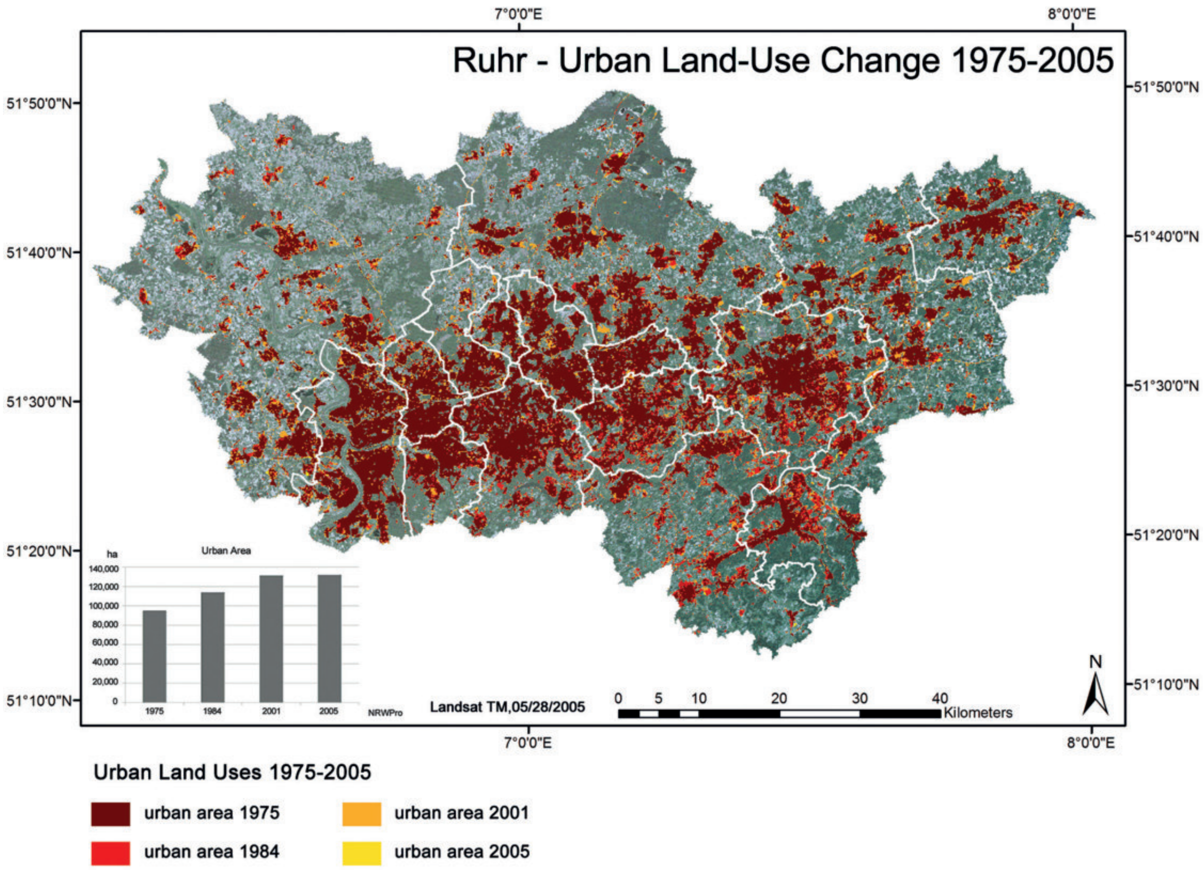

Fig. 3: Urban growth of the Ruhr 1975–2005 (derived from NRWPro data set)

While the NRWPro data are 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 region includes 53 zones which identify different semiotic systems, coverage dates, and durability. Instead of these zonings, we apply the international inter-comparable European Urban Atlas developed by the European Environment Agency (EEA) (Fig. 2). The European Urban Atlas is a part of the local component of the GMES/Copernicus land monitoring services and based on high-resolution earth observation data. This data set exhibits a minimum 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 within the data set, the system includes useful land use classes.

Table 1 provides an overview of the various land use descriptors within the three data sets that are associated with land uses that include potential residential areas on greenfields. RuhrFIS defines agricultural areas, meadows, pastures, forests, and other as potential residential areas on greenfields (REGIONALVERBAND RUHR 2011). Accordingly, pixels containing any one of these land-use classes were extracted from the urban atlas. In order to ensure thematic consistency among the applied data sets, the pixels extracted from the RuhrFIS classification were compared to the 2005 NRWPro data set. Pixels classified as "urban" in NRWPro were discarded. The same procedure was used for "forest" pixels. Urban development within forested areas is rarely considered in most regional planning, even though forests represent a high fraction of the total land cover in the Ruhr (Goetzke 2012; REGIONALVERBAND RUHR 2011; Siedentop and Kausch 2004; Ulmer et al. 2007). Including a forest class in the modelling procedure would reduce the significance of the map of potential residential areas.

Tab. 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

3 The artificial intelligence of cells and agents

3.1 ReHoSh–MAS simulation of urban decline

The MAS ReHoSh focuses on the dynamics of interregional housing markets to infer the development of population patterns, housing prices, and housing supply in shrinking city agglomerations (Fig. 1). The object-oriented implementation of ReHoSh in the Repast© open-source software package (Railsback et al. 2006) provides a computing environment within which ReHoSh operates quite efficiently. Typical ReHoSh processing is completed in approximately two minutes–a very short period compared to other complex urban system models (Benenson and Torrens 2004; Lee 1973; Wegener 2011).

Table 2 presents the key elements of ReHoSh and the main prerequisites of the simulation framework (Couch et al. 2005; Hannemann 2002; Macal and 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 in the real estate markets including 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) (Ajzen 1985; Benenson and Torrens 2004; Kalter 1997; Koch and 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). Households can also compete with each other. Those residing in a target city have established a social network there and have an advantage (Jain and Schmithals 2009; Thomas et al. 2008). Furthermore, decisions made by household agents stimulate reactions from the city agents.

The city agents can modify the housing-related factors according to the economic theories of the equilibrium price (Mankiw and Taylor 2004), price elasticity (Hilber 2007) and the "hog cycle" thereby equating the current housing supply to the demand from two years previous (Arentz et al. 2010). This reflects the inertial reaction of the housing market to changing demand conditions. The housing quality of a city is also impacted by the absolute amount

Tab. 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

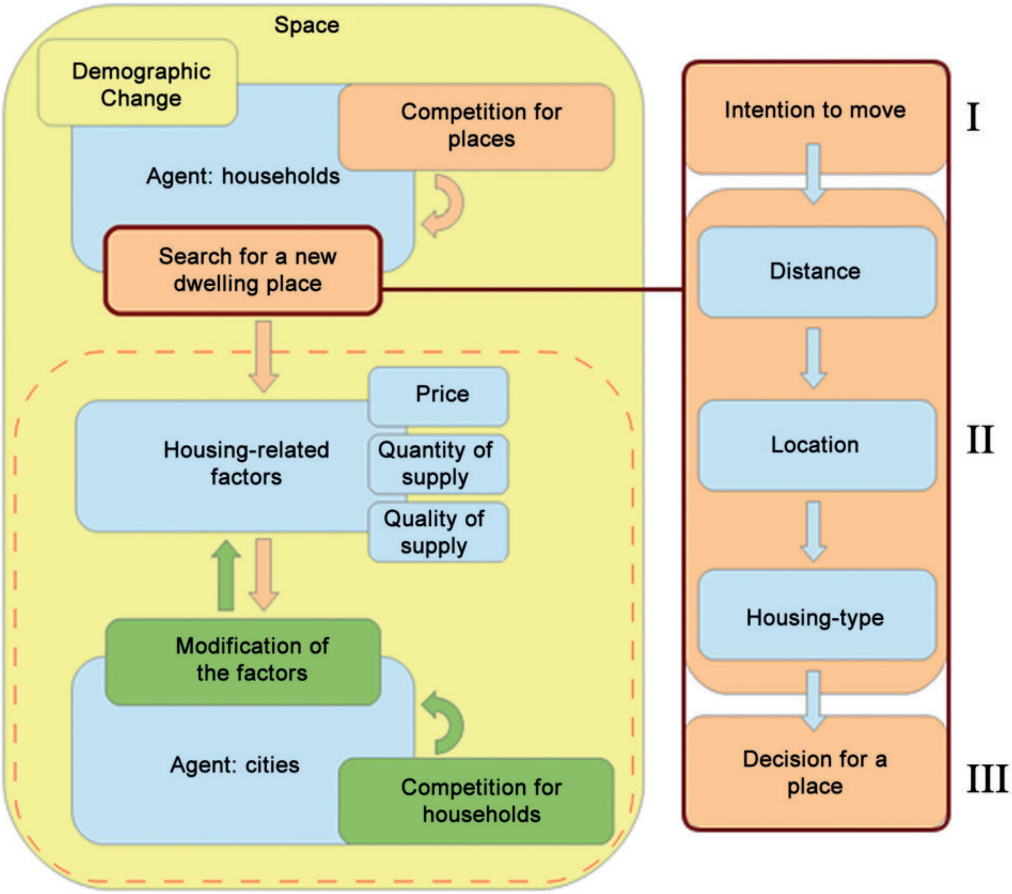

Fig. 4: Main concept of ReHoSh: the left section of the graphic shows the model's agents, interactions, and key factors. The three-step search by households for a new dwelling place is shown at the right

of ongoing housing demolition–or "tear-down" (Dransfeld 2007; Heimpold and Ebert 2012). Additionally, cities can increase housing supplies as a reaction to neighboring cities' behavior (Spiegel 2004). Equation 1 shows how the total attractiveness of a city is determined; this value is used to simulate the actual individual decision for new housing. Beside housing price level and supply, the qualitative attractiveness of the available housing stock is calculated. This is related to individual community vacancy and demolition rates. Hence, the feedback loop between household migration, vacancies, and price development is incorporated.

Table 3 contains the implementation values of ReHoSh for the start year 2010 (BORISplus.NRW 2012; IT NRW 2013; REGIONALVERBAND RUHR 2011). The calibration and validation procedure of ReHoSh is described in Rienow and 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 and Schlömer 2003; Danielzyk 2006; Grüber-Töpfer et al. 2008; IT NRW 2013; REGIONALVERBAND RUHR 2011; Westerheide and Dick 2010). Rienow and Stenger (2014) demonstrate that ReHoSh is able to capture

$$totalA^{t} = \frac{priceF * priceA^{t} + quantityF * quantityA^{t} + qualityF * qualityA^{t}}{priceF + quantityF + qualityF} * households^{t} \quad (1)$$

totalA = *Total attractiveness of the city*
priceA = *Attractivenessoftheprice*
quantityA = *Attractivenessofthequantityofsupply*
qualityA = *Attractivenessofthequalityofsupply*
priceF = *Weightingfactoroftheprice*
quantityF = *Weightingfactorofthequantityofsupply*
qualityF = *Weightingfactorofthequalityofsupply*
households = *Total number of households of the city*

Tab. 3: Base data input of ReHoSh for the year 2010

City/ District	Number of households (x100)			Number of dwellings (houses and apartments)	Purchase prices (€/m²)		Potential residential area (ha)
	1-2 pers, < 45 yrs.	1-2 pers, ≥ 45 yrs.	≥ 3 pers.		land[i]	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

[i] Land values represent the cost to develop land from non built-up to built-up area

the interaction between household movements in total and price development in the Ruhr at a minimum reliability of 90%.

3.2 SLEUTH–A cellular automaton of urban growth

Clarke's UGM (generally known as SLEUTH), was developed by Clarke et al. in 1997. SLEUTH is an acronym of the model's initial input factors of *slope, land use, exclusion, transport, and hillshade* (Fig. 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. These are *spontaneous growth*, reflecting the random emergence of new urban areas; *new spreading center growth; edge growth* depicting urban sprawl, and; *road-influenced growth* (Fig. 5).

One growth cycle represents one year and consists of the four rules listed above. 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 (described in detail in Section 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, or MRV (Pontius et al. 2008) and implemented it within XULU© (eXtendable Unified Land Use Modeling Platform). XULU is a JAVA-based modeling environment developed at the University of Bonn (Goetzke and Judex 2011; Schmitz et al. 2007). Goetzke (2012) applied UGMr for a simulation run for the entire NRW region of and compared it with the original UGM defining the growth coefficients with the Lee-Sallee index (Clarke et al. 1997). Besides showing

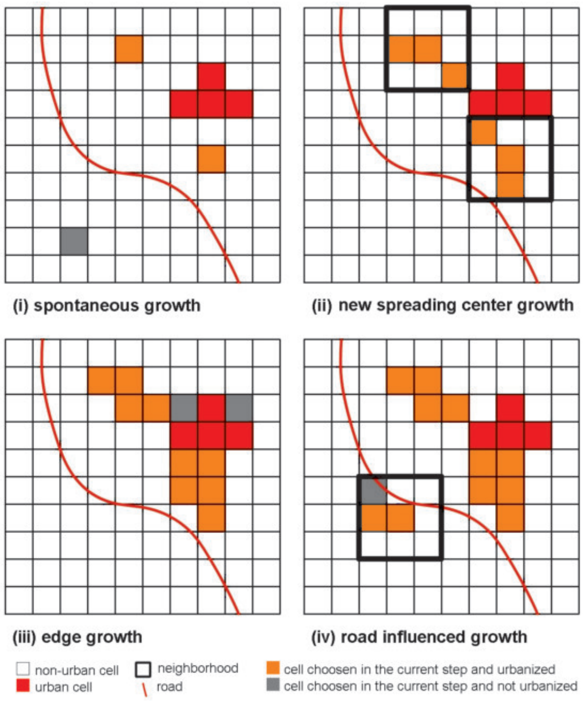

Fig. 5: Growth types of a growth cycle in UGM

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 and 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 required. UGMr has some limitations, however. While performance is very high, the UGMr modeling process is strongly influenced by stochastic decisions, which result in variable spatial patterns. UGMr also produces no information regarding the human and ecological forces driving local suitability of urban growth. Here, the combination of UGMr with a suitability map is a reasonable approach for guiding the CA (Mahiny and Clarke 2012; Rienow and Goetzke 2014).

3.3 SVM–Support Vector Machines as CA conditioner

Rienow and 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. 1). SVM are based on a machine-learning concept developed for solving classification problems (Cortes and Vapnik 1995; Vapnik 1998). Fundamentally, 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 *a priori* knowledge. The input vectors are reprojected 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:

$$\min_{w,\,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i$$

$$\textit{subject to } y_i(\langle w, x_i\rangle + b) - 1 \geq 0 \textit{ for } i = 1, \ldots, n \qquad (2)$$

y_i = *class label (e.g. urban growth, non-urban growth)*
x_i = *data point in n-dimensional feature space*
w = *normal to the seperating hyperplane*
b = *bias*
C = *penalyty 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 and Münter 2008; Siedentop and Fina 2010; Verburg et al. 2004a). It consists of distance variables, density measurements, and dasymetric maps (Tab. 4). Thus, the layer stack reflects the "location-specific characteristics" of every cell (Verburg et al. 2004a, 146). While the risk of incorrect cross-level deductions in terms of ecological fallacy is reduced, it is not totally eliminated (Robinson, 1950).

The SVM model is compiled utilizing the imageSVM© software package, developed at Humboldt University in 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 of 1 km between equal pixels is used (Lesschen et al. 2005). The probability map is calculated according to Platt's probability function (Platt 1999; Wu et al. 2004).

Tab. 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 residential 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

Following, the SVM probability map of urban growth (Fig. 6) is combined with the exclusion layer of UGMr (Rienow and Goetzke 2014). The CA is then calibrated; the stochastic nature of the CA is reduced by using 100 Monte Carlo iterations (MC). A probability of 33% is used as cut-off value to transform CA output into a binary land-use map (Rafiee et al. 2009; Wu et al. 2008). At this 33% probability level, the reliability of UGMr-SVM in terms of stochastic variability is a certainty (Aerts et al. 2003; Langford and Unwin 1994; Wegener 2011). The calibrated growth coefficients of UGMr-SVM are presented in table 5. Validation results which were achieved are considered to be at a "very good" level regarding the probability performance (ROC), when compared with values of randomness (Cohen's Kappa), quantity estimations ($\varkappa_{histo}$), allocation ability ($\varkappa_{loc}$), and urban growth "fuzziness" (MRV) (Lauf et al. 2012; Messina et al. 2008; Pontius et al. 2004; Ruiz et al. 2012; Rykiel 1996).

4 Coupling cells and agents for modeling the urban future

4.1 Weighting urban growth with agents

A drawback of UGMr is its "black-box" approach to the calculation of urban growth rates. Implementation of SVM reduces this perceived shortcoming. Using drivers of local urban-growth suitability provides the CA with a kind of theoretical

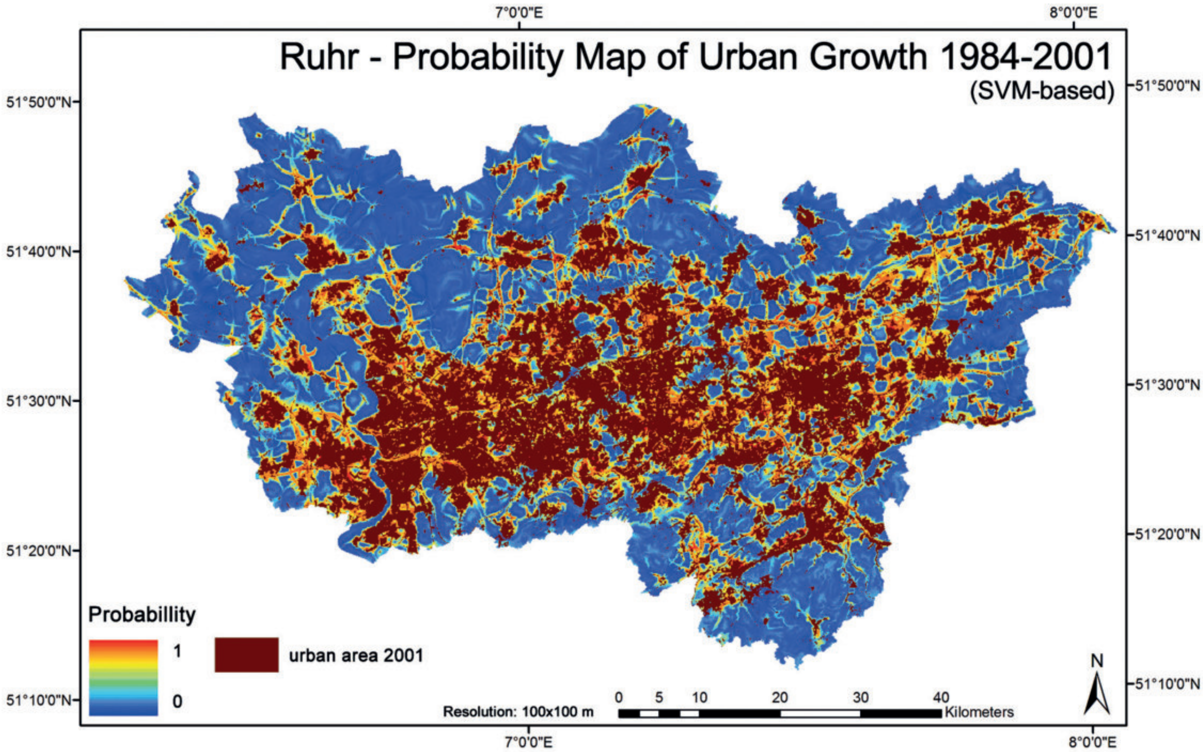

Fig. 6: SVM probability map of urban growth 1984–2001

foundation (Briassoulis 2000). The growth coefficients of UGMr, however, 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 a specific UGMr self-modification option that assumes a non-linear, s-curve growth type (Clarke et al. 1997). Relationships to dynamic state changes in the coupled human/environment are not incorporated. Hence, macro-level conditions and constraints are disregarded as much as micro-level decisions and their realizations. ReHoSh is designed to capture changes in behavior of its stakeholders that have an effect on future construction rates and local housing preferences within the urban environment. The potential number of new dwellings within a community is dependent on a process of individual (and collective) decision making that occurs beyond the discrete dimension of a pixel. Spatially implicit information must be disaggregated to spatially explicit guidance as well as demand parameters for UGMr. In this study we introduce the concept of *semi-explicit urban weights* for moderating between the extremes of demand and supply, pattern and process, society and space, as well as pixels and people. We define semi-explicit urban weights as the simulated dwelling supply, varying on community level, assigned to cells identified as potential residential areas. Thus, the probability of new housing construction is disaggregated from the community level and rescaled to areal units that encompass relevant land uses.

Tab. 5: Growth coefficients and validation results 1975-2005 of UGMr-SVM

Growth Coefficients	Slope	90
	Dispersion	3
	Breed	4
	Spread	4
	Road	80
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 ReHoSh simulation was carried out within the context of a standardized "business-as-usual" development scenario implemented to predict and update 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.

$$P_{uw_{ij}} = \frac{S_{sim_j}}{S_{pot_{ij}}} \tag{3}$$

The results are assigned to the selected land use classes of the Urban Atlas (described in Section 2.2). This map is then merged with the SVM probability map. The total probability of urban growth of cell i in community j is therefore $P_{total(ij)}$:

$$P_{total_{ij}} = \frac{P_{SVM_i} + P_{uw_{ij}}}{2} \tag{4}$$

where: $P_{SVM(i)}$ are the SVM-based probabilities derived from the location-specific characteristics for a cell i.

Figure 7 presents maps of the semi-explicit urban weights (7a) and the total probability of urban growth (7b).

The value range of the semi-explicit urban weight values is lower than that of the SVM probabilities (Fig. 6). In order to maintain the calibrated growth rate of 3,995 ha for the year 2025 (along with the proportions of the various growth types) as predicted in the "business as usual" scenario, the CA coefficients of UGMr were adjusted empirically by a value of 10 (Tab. 5).

4.2 Three future scenarios of the Ruhr

The ReHoSh household preferences are the "set screws" used to implement alternative 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 discussed above, two additional scenarios–"sustainable thinking" and "dream of owning a house"–are introduced. Both outline altered housing preferences, where the initial impulse for a change in behavior could be thought of as a sort of governmental subsidy, like the reintroduction of the "Eigenheimzulage", revised tax rates, or rent limits (Hirschle and Schürt 2008; Mielke and Münter 2008). The first scenario reflects the "30 hectare directive" set by the German Federal Government in an attempt to reduce the daily rate of conversion of open land to settlement and traffic areas (Hoymann et al. 2012). This scenario assumes that residents are motivated to implement the sustainable handling of the limited land resource. The "dream of owning a house" scenario addresses the promoting of the steady desire of families to own homes in sub- and exurban areas. It identifies the development of new semi-detached housing settlements as one of the critical drivers of urban sprawl in Germany (Dittrich-Wesbuer 2008; Hirschle and Schürt 2008; Mielke and Münter 2008; Siedentop and Fina 2008). A suite of three scenarios is reasonable as this number is "…adequate but not overwhelming; brief but not oversimplifying…" (Xiang and Clarke 2003, 899). It should be emphasized that the "business as usual" scenario should not be regarded as the most probable. This scenario is simply a linear prediction of current conditions based upon historic information within a complex urban system where business is never "as usual".

Table 6 depicts the housing 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 this minority household group–as well as in the largest group (1–2 pers, ≥ 45 yrs.)–shows a 5% increase under "sustainable thinking" scenario and 5% decrease under the "dream of owning a house" scenario. All other parameter settings of ReHoSh are maintained, including migration probabilities of the various household types, their preferred distances, or the demolition and vacancy rates of the different cities.

4.3 Modeling urban growth by coupling CA with MAS

Results of the simulations show an overall decrease in the number of Ruhr households in 2025. The general trend of demographic decline simulated by the MAS can be observed with only slight deviations in all scenarios, and is in agreement with recent regional demographic forecasts as well (Grüber-Töpfer et al. 2008; Siedentop and Fina 2008). Table 7 includes the P_{uw} values (Eqation 2) for every community of the Ruhr under each of the three scenarios for 2025.

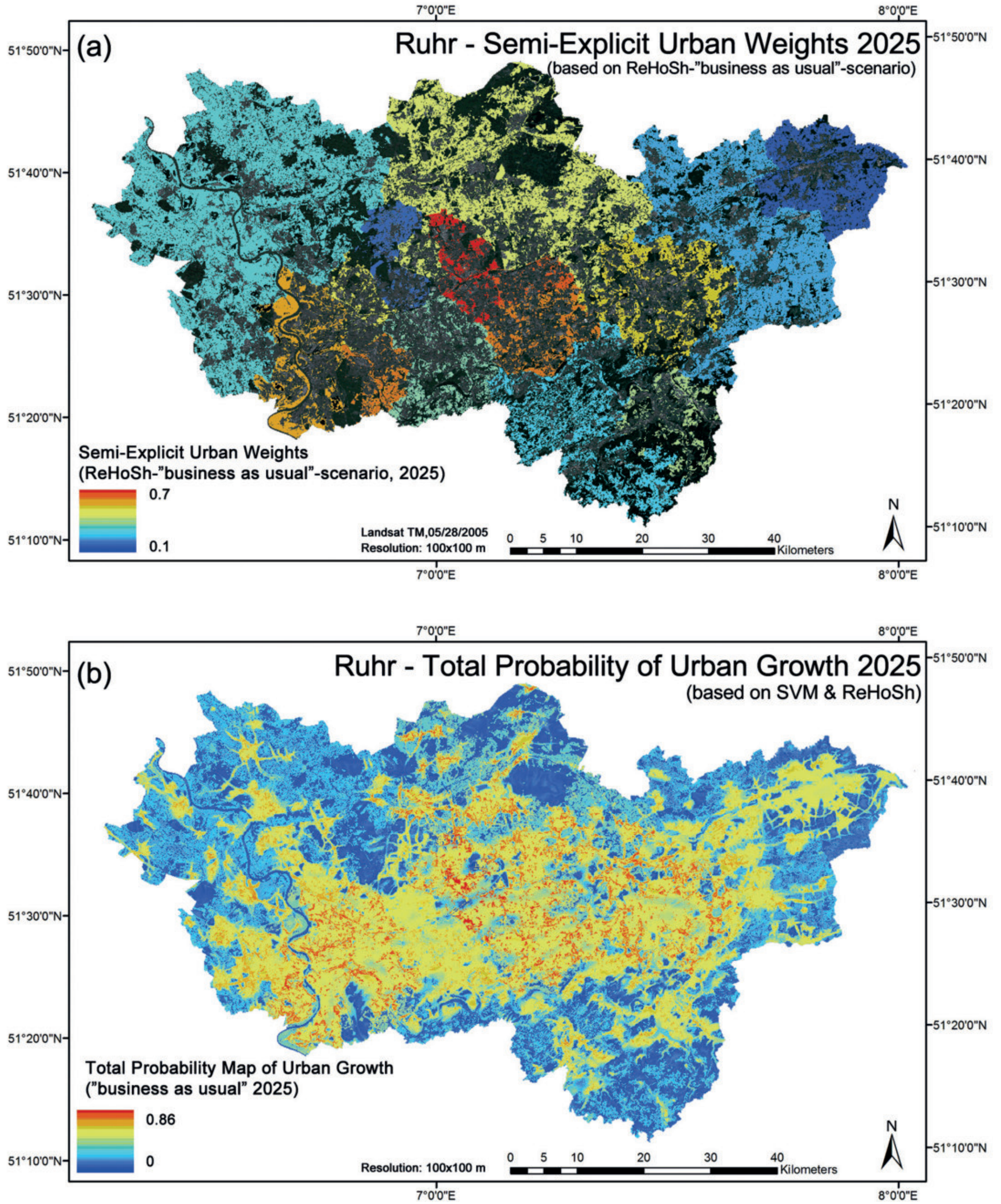

Fig. 7: (a) Map of semi-explicit urban weights ("business as usual"); (b) Total probability of urban growth ("business as usual")

Households decrease under all scenarios in numbers similar to those in the "business as usual" scenario depicted above. Land conversion proceeds under all scenarios. Simulations show that the conversion of the majority of potential residential areas in the cities of Essen and Gelsenkirchen takes place under the initial "business as usual" scenario. Here, the simulated difference generated within the "sustainable thinking" scenario exceeds the actual changes in the preferences for new dwellings (Tab. 6). Under

Tab. 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 households is defined by the age of the head of household

the "dream of owning a house" scenario, all cities effectively convert their entire potential residential area; only the cities of Hamm and Bottrop (as well as the four rural districts) are exceptions.

The ReHoSh-scenarios of changing housing preferences were incorporated into UGMr-SVM using the total probability maps. The growth coefficients of the CA, as adjusted for a ReHoSh "business as usual" scenario (detailed in Section 3.3), were maintained for the other two scenarios, as was the critical cut-off value of 33, after 100 MC. Figure 8 presents the scenario results of the coupled CA-MAS model for the Ruhr in 2025. In the "business as usual" scenario urban areas had an extent of 132,012 ha in 2005, increasing to 136,007 ha in 2025. The "sustainable thinking" scenario yielded a 2025 urban extent of 134,285 ha, a reduction in the growth rate of 2,273 ha below that shown by the "business as usual" scenario. The "dream of owning a house" scenario produces a 2025 urban extent of 140,141 ha, an increase over the "business as usual" scenario of 8,129 ha. Those cells urbanized in the scenario with the lowest growth rate ("sustainable thinking") are identified as urbanized in the other two scenarios as well. Only a small number of cells are identified as "urban" in a single scenario. It is readily apparent

Tab. 7: Semi-explicit urban weights calculated by ReHoSh for the year 2025

	Change in 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

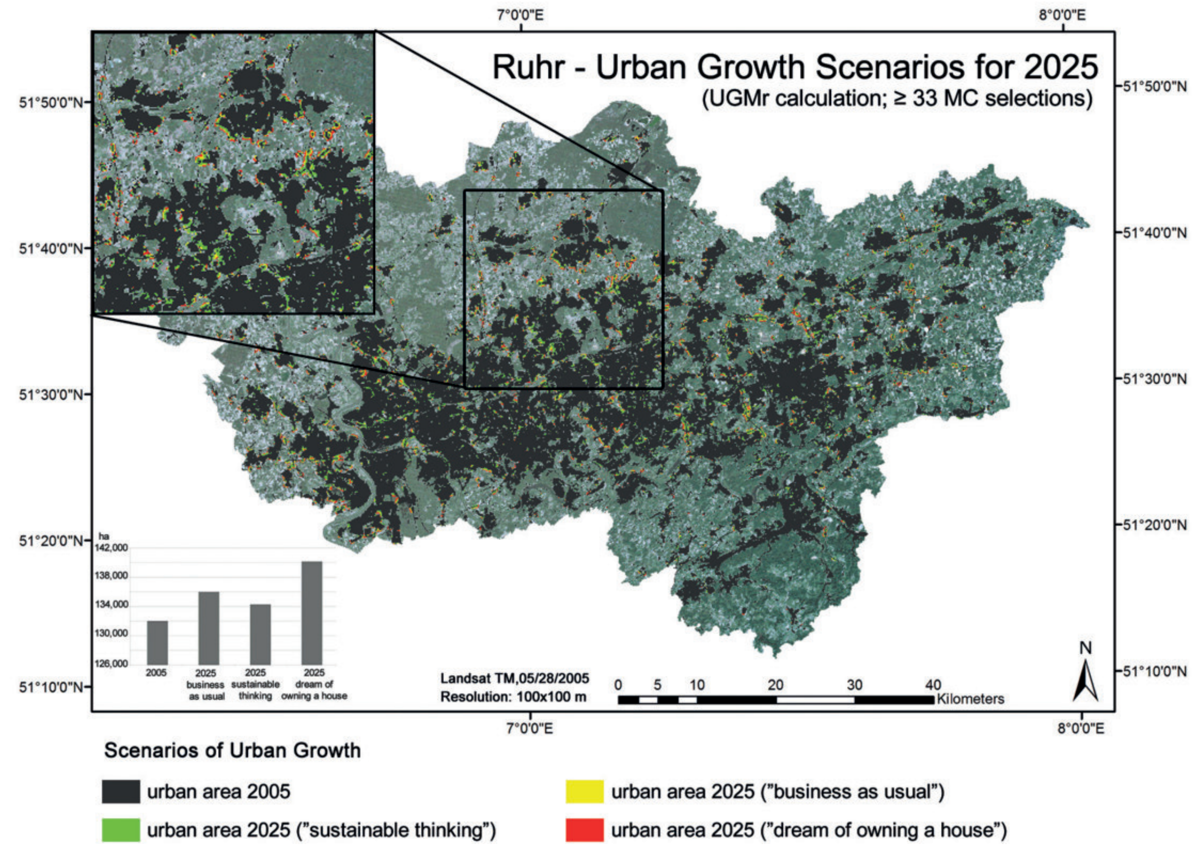

Fig. 8: Three scenarios of urban land-use configuration of the Ruhr in 2025

that the free "open" spaces between neighboring urban cells are the first areas to be urbanized (Fig. 8, "sustainable thinking"). The increased growth rates depicted in the "business as usual" and "dream of owning a house" scenarios are consistent through the Ruhr study area and lead to more extensive urban land conversion within even relatively remote areas of the region.

The question of how the different scenarios influence the spatial extension of the Ruhr's urban growth will be analyzed within the concept of urban DNA (Silva 2004). Analogous to biological DNA, the urban DNA concept postulates fundamental elements that are common to each urban area and determine their future growth pattern (Silva and Clarke 2005). Accordingly, geographical problems are assessed in a uniform representation of space with a homogenous geographic variability. Gazulis and 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 UGMr grid input (described in Section 3.2), including an urban land use map, a slope layer, the transport network, as well as an exclusion layer (Fig. 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 replaced by the three total probability maps of 2025 urban growth of the Ruhr. 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.

For every scenario UGMr-SVM is run with the calibrated growth coefficients and 100 MC iterations (see Sections 3.3 and 4.1). This allows observation of

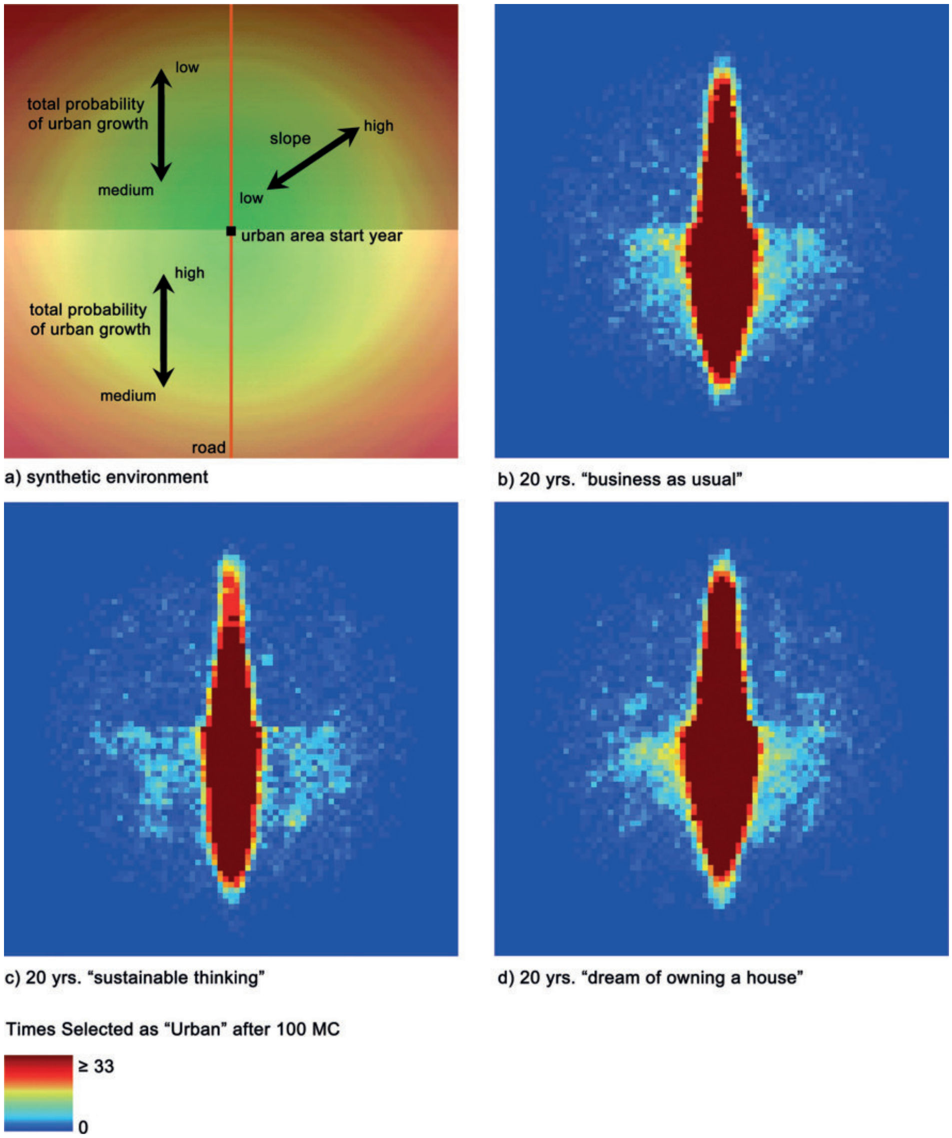

Fig. 9: Urban simulation in a digital petri dish consisting of the fundamental elements of the Ruhr's urban area

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. UGMr-SVM calculates and allocates the highest amount of urban growth under the "dream of owning a house" scenario. While the pattern is similar to the "business as usual" assumptions, it is at variance with "sustainable thinking" assumptions. Here, the urban pattern is both narrow and less dispersed. Generally, the DNA of the Ruhr's urban areas is characterized by a propensity for edge growth and a significant influence of the road network. Areas of low growth probabilities will still be subject to urban growth along the road within the northern part of the synthetic region. In contrast, these areas avoid the "sprawled" urban dispersal pattern that is seen in the southern portion of the synthetic region.

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. We examine the potential of coupling two AI strengths: the ability to do *ad hoc* urban growth modeling; and the simulation of individual decision-making that interacts on several organizational levels. By simultaneously modeling from and to the pixel, the CA-MAS approach captures 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 along with historic land-use information to model different types of urban growth. 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 in regional 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. Using the inter-comparable European Urban Atlas, the concept of semi-explicit urban weights was developed. This served as a locational background within which spatially implicit MAS information about new housing constructions was transformed into the gridded environment of a CA. It also enabled the simulation of different scenarios reflecting changes in the society as a whole. They illustrate the effects of a 5% positive or negative change in preference within two household groups regarding newly developed housing. The total probability maps derived under "sustainable thinking" and "dream of owning a house" scenarios show clearly the differing effects of these two scenarios upon future rates of UGMr-SVM. Their spatial impacts are visualized with the concept of urban DNA and a "digital petri dish", thus revealing the generic growth elements of the Ruhr's urban areas.

Though the CA-MAS combination described here constitutes an innovative approach, it exhibits some limitations. Most importantly, UGMr-SVM is constructed exclusively for modeling spatial growth. The pattern dynamic of urban perforation (Siedentop and Fina 2008) is not addressed nor simulated in a spatially explicit manner. A closer examination of our specific simulation conditions reveals that this is a minor limitation. While the process of building demolition is an important issue for city planning in the Ruhr, the resultant phenomenon of urban perforation will not carry a significant effect at the 100 meter spatial scale used in this analysis (BBSR 2012; Hostert 2007; Kroll and Haase 2010; Siedentop and Fina 2008). ReHoSh, however, does incorporate demolition and vacancy rates as influences on the quality of housing supplies within communities. And, again, along with other factors, housing quality influences the decision of households regarding a new dwelling in a particular community. Accordingly, a feedback loop is established between migration, vacancies, and house price development in order to define the consequences of a contraction in the housing supply in a spatially implicit manner. A second significant limitation is the focus by ReHoSh exclusively on the housing market. Developments in industrial, retail or other urban uses are not directly included in the model. 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 these other uses are only indirectly included in the overall CA-MAS compound. Thirdly, ReHoSh assumes a constant household structure, and information regarding social segmentation or separation and lifestyle changes (including overall reduction in average family size) 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 which will allow researchers to improve the understanding of patterns and processes of urban growth. Further research should focus on the extension of the ReHoSh model to include commercial land use and transport systems as well as segmenting city agents into real estate managers and administrative members. These developments will serve to enhance the creditability of ReHoSh. Apart from the housing preference variable, other parameters may be modified in order to identify additional potential scenario effects. Additionally, it remains a challenge to integrate and synchronize the dissimilar spatial and temporal scales of UGMr and ReHoSh. The coupling solution we have presented here treats the agents' decisions on aggregated spatial and temporal levels; the conversion of an image pixel as well as the decision making of an agent both occur discretely after one year. An approximation of modeled events at the daily temporal scale would be desirable. Finally, additional inclusion of stakeholders and decision makers is an important future direction for research on this topic. Although the "soft" AI combination presented here may be advantageous to communicate a visual sense of how an alternative future might look, the approach would be enhanced if it allowed users to readily enter new decision rules or revise the behavior of urban agents. It would then be possible to more comprehensively investigate, discover, and describe the behavior of complex urban systems as they react to changing global conditions.

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