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An easy-to-use spatial simulation for urban planning in smaller municipalities

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ABSTRACT

In order to produce precise outcomes, most spatial simulations require great volumes of data input, intensive data preparation or programming skills. Consequently, high quality spatial simulations are usually not applied in practice in municipalities of smaller size (< 25,000 citizens). This study aims to provide an easy-to-use tool for smaller urban administrations. A web application was developed which requires a minimum of manual user input for automated data preparation. Gamified elements aim to encourage the user to experience the underlying mechanisms of the system under alternating planning scenarios. These mechanisms are modelled as a combination of spatially implicit and explicit rules which can be derived from dependencies in the data itself. Spatial attractiveness was modelled as a function of accessibility of facilities, ground value, soil sealing, traffic intensity and noise pollution in a multi-variate spatial autoregressive regression analysis. A case study for the city center of Herdecke (Germany) revealed that the establishment of a new event location in the northern part of the study area was most appropriate for increasing spatial attractiveness. The presented easy-to-use tool is suitable for practical application in everyday administrative processes of smaller municipalities and thereby contributes to more applied sustainable urban planning.

1. Introduction

In the 21st century, urban decision makers find themselves simultaneously faced with a plethora of interconnected societal and ecological challenges. These challenges comprise, for instance, consequences of demographic change (Champion, 2001; Danielzyk, Meyer, & Grüber-Töpfer, 2010), demand-adapted local supply with basic services (Libbe, Köhler, & Beckmann, 2010), progressive soil sealing and its multi-scale effects on urban heat islands and heavy rains (Arnfield, 2003; Oke, 1973; Tyrna & Hochschild, 2010). Spatial decision support tools can provide informative assistance for urban planners and policy makers in order to meet the interconnected challenges of complex urban systems and to estimate consequences of specific planning strategies. In the last 70 years, various spatial simulations were created within the fields of system dynamics and agent-based modeling.

The former dates back to the 1960s, when it was founded by Forrester (1969) at the Massachusetts Institute of Technology. It models circular causalities with reinforcing or extenuating feedback loops, which are usually spatially implicit (Scholl, 2001). Examples for system dynamics modeling platforms include Vensim (Ventana Systems, 2015), Powersim (Powersim Software, 2017) and Stella (isee systems, 2017).

Agent-based models (ABM), also called individual-based or multi-agent models, represent the second large research strain regarding system simulations. It dates back to the first cellular automata (CA) in the 1940s which – after the astonishing results of the game of life CA - experienced a renaissance in the 1970s when it was used in many disciplines (Gardner, 1970; Janssen, 2005). In recent years, CA models have been applied in various research fields such as savanna fire propagation (Berjak & Hearne, 2002), vegetation distribution and desertification (Kéfi et al., 2007), land cover and land use changes (Verstegen, Karssenberg, van der Hilst, & Faaij, 2014) and urban development (Batty, 2005; White & Engelen, 1993). Recent developments in this field of research include, for instance, CA models with varying cell shapes (Pinto, Antunes, & Roca, 2017), considering modeling uncertainties (Şalap-Ayça, Jankowski, Clarke, Kyriakidis, & Nara, 2018), patched-based logistic regression (Chen, Li, Liu, & Ai, 2014) and Bayesian CA approaches (Verstegen et al., 2014; Verstegen, Karssenberg, van der Hilst, & Faaij, 2016). “Agent-based models consist of a space, framework, or environment in which interactions take place and a number of agents whose behavior in this space is defined by a basic set of rules and by characteristic parameters” (Scholl, 2001, p. 2). Reynolds (1999, on his web page) further sets out that “there is an

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overlap between individual-based models and cellular automata" and that "cellular automata are similar to spatially-explicit, grid-based, immobile individual-based models". In these models, the overall systemic patterns emerge from behavior of individual agents. This behavior is usually defined by a simple set of rules which, in most cases, is probabilistic and spatially explicit. Agent-based models have recently been applied to model, for instance, pedestrian movements in urban contexts (Omer & Kaplan, 2017), movements of individuals during an evacuation scenario (Tan, Wu, & Lin, 2015) and tenants' choice of residence within a city (Shirzadi Babakan & Alimohammadi, 2016). Examples of platforms for modeling ABMs include RePast (Collier, 2003), SWARM (Minar, Burkhart, Langton, & Askenazi, 1996), Echo (Forrest & Jones, 1995), Boids (Reynolds, 2001), CORMAS (Bommel, Becu, Le Page, & Bousquet, 2016) and MASON (Luke, Balan, Sullivan, & Panait, 2015).

As research in the fields of system dynamics and agent-based models was strikingly isolated from each other until the early 2000s, there was a general call for mixed models in order to exploit the advantages of both modeling approaches (Macal, 2010; Nava Guerrero, Schwarz, & Slinger, 2016; Scholl, 2001). Since then, various mixed models, which are also called multimethod models, have been presented, such as MASGISmo (Gebetsroither, 2010) NetLogo (Uri Wilensky, 2016), AnyLogic (AnyLogic, 2014), Nova (Salter, 2013) and an intercity transport model (Lewe, Hivin, & Mavris, 2014). All of these modeling platforms, however, require great volumes of data input, intensive data preparation, programming, modeling, analysis, GIS or other specialized technical skills (Nava Guerrero et al., 2016).

A deficit in financial and staff resources is a universal phenomenon among small administrations (< 25,000 citizens). Consequently, spatial simulations are usually not applied in practice in municipalities of smaller size and systemic feedbacks and respective reasonable and evidence-based measures are usually not considered for planning strategies and policies in these communities (Janssen & Ostrom, 2006; Pullin & Knight, 2003; Pullin, Knight, & Watkinson, 2009; Russo, Lanzilotti, Costabile, & Pettit, 2018).

One approach to overcome these restraints of spatial simulation for the application in everyday urban panning routines is the "gamification" or "serious game" approach (Ahlqvist, Khodke, & Ramnath, 2018). It picks up findings from the field of psychology which indicate that rather than instruction, the most efficient way to comprehend complex matters is by personal experience and by evoking the learner's curiosity (Deterding, Sicart, Nacke, O'Hara, & Dixon, 2011). As games provide both, the gamification approach puts complex and serious topics into an easy-to-use and enticing game environment (Deterding et al., 2011; Ingensand et al., 2015; Prensky, 2003). The user is rewarded for appropriate action with motivational affordances, such as game scores, which aim to trigger psychological and, ultimately, behavioral outcomes (Hamari & Koivisto, 2014).

Another drawback of most decision support tools for urban planning is a predominant technical perspective rather than addressing the overall well-being of citizens which is the main objective of urban planning (Nam & Pardo, 2011; Neirotti, Marco, Cagliano, Mangano, & Scorrano, 2014). However, the level of self-perceived well-being and if citizens feel comfortable within the given space is highly subjective, individually different and geographically bound. This raises the question as to how spatial attractiveness can be quantified, compared and best integrated into an easy-to-use spatial simulation.

1.1. Objectives and structure of the paper

This present study aims to integrate geospatial methodologies for measuring spatial attractiveness (Section 2.2) with various geo data sources (Sections 2.3, 2.4) and combines gamification (Section 3.1), system dynamics (Section 3.2) and agent-based modeling (3.3) approaches in a novel, easy-to-use platform for creating spatial simulations for urban systems (SimUSys). In this context, an urban system is defined as the construct of all interconnected social, environmental and technical entities within a city which can be quantitatively expressed and for which data is provided (see Section 5 for a discussion on incorporating qualitative approaches). It aims to deploy as of yet underexploited synergies of the individual approaches from a geospatial perspective.

A web-based user interface which requires no local installation allows planners with no technical geospatial skills to simulate various planning measures such as the establishment of a new facility of basic goods and services and the resulting systemic effects for e.g. the spatial attractiveness for a city district. It thereby investigates whether the methodological synergies allow for practical application and consideration of complex systemic feedbacks in everyday planning routines. Moreover, it thereby supports knowledge transfer and mainstreaming of technical learnings. A high usability for non-technical users is accounted for by, for example, integrating methods for automated geospatial data preparation.

In accordance with the gamification approach, users get incentives to evaluate planning strategies, for example, by game scores. In addition, the model parametrization is straightforward as the rules for this mixed model can be derived automatically from influences and dependencies in the data itself using geographical regression methods. These models influence the simulations which can be created with the SimUSys platform, as they can be used to define the behavioral rules of the agents (Section 3.3).

In a case study, it is shown how SimUSys can be used to build a simulation for the identification of facilities with the highest influence on spatial attractiveness and the most suitable site for a new facility (Section 4). The SimUSys platform for creating urban simulations was set up in cooperation with city planners and its layout is applicable by administrations of smaller municipalities but in principle, it is scalable to other urban and regional planning contexts.

2. Methodology and data

A platform for creating spatial simulations was created which makes use of the gamification approach and is straightforward to access, set up and use for evaluating different planning strategies. The following sections describe how the main benchmark for this evaluation, the spatial attractiveness, was measured (Section 2.2) for a use case in Herdecke in Western Germany (Section 2.1) and how a multitude of data sets were automatically integrated (Sections 2.3, 2.4) in order to investigate influences and dependencies.

2.1. Study area

The city of Herdecke is located at the southern rim of the metropolitan Ruhr-Area in Western Germany, south of the larger cities of Bochum and Dortmund. The Ruhr-Area is an urban agglomeration of eleven metropolitan cities and four administrative districts incorporating a total of 53 communities. It covers an area of ~ 4436 km^2 and is inhabited by ~ 5 million citizens which results in a population density of about 1200 citizens per km^2 (Regionalverband Ruhr). The city of Herdecke itself covers an area of about 22 km^2 and is inhabited by ~ 25,000 people (IT.NRW, 2017), resulting in a population density of ~ 1100 citizens per km^2. The cities administration employs 265 people in total, and the department for construction and planning is run by 4 people (City of Herdecke). This number of staff is typical for a city of this size in this region and does not allow for elaborate data preparation, programming and validation of urban system simulations in everyday planning routines. SimUSys was set up in cooperation with Herdecke's city planners. Their user demands were that in order to exploit insights into system behavior for more effective and sustainable practical application, SimUSys had to be easy-to-use and its results intuitively comprehensible.

2.2. Measuring spatial attractiveness

The overall benchmark for simulations created with SimUSys is the level of self-perceived well-being of citizens within the given space. This concept is defined as "spatial attractiveness". As it is highly subjective and individually different, measuring this parameter is an intricate task. In (Mueller, Klein, & Hof, 2016b) a methodological framework was supposed for measuring spatial attractiveness. A web map application was designed which allowed citizens to define places in which they would "feel good" or "not feel good" using a topographic base map. This application was promoted by the local press and the survey was carried out at two Christmas markets in Herdecke. In addition to the web map application, a printed map could be used by the participants (Mueller et al., 2016b). The collected data on spatial attractiveness was aggregated to an analysis grid with a cell size of 100 m × 100 m for comparison with additional data and modeling influences.

2.3. Automated data integration

Additional data was collected from the federal state of North Rhine-Westphalia and its public company for road maintenance ("Strassen NRW"), the cities association of the Ruhr-Area ("Regionalverband Ruhr"), the administrative district of "Ennepe-Ruhr Kreis", the residents' registration office of Herdecke, the city's administration itself, OpenStreetMap, as well as self-acquired data. Data comprised spatial and attributive information which can be subsumed under the headings of (1) "environment and services", such as land use, protected areas, waste water treatment plants, …, (2) "networks", such as streets, paths, pipelines, …, (3) "points of interest" (POIs), such as parks, grocery stores, event locations, …, and (4) "planning entities", such as administrative districts, zoning plans, addresses. The collected data constituted various data models, types and formats with different coordinate systems, geometries and writing conventions.

In order to use this broad data for investigations about influences on spatial attractiveness, a tool for automated data integration was created (Mueller, Klein, & Hof, 2016a). This tool is easy-to-use and solely requires a directory path to the inhomogeneous data collection and an output location to which the combined and integrated data should be saved to (Fig. 1). The tool makes use of tabular catalogues which are easily expandable by the user with standard office software. Using this tool for automated data integration, coordinate systems were consistently re-projected, files renamed, geometries converted and repaired, missing data gathered from external open data sources, geodatabases extracted, features and attributes combined, duplicates and special characters removed, networks created and addresses georeferenced. Ultimately, all data sets were aggregated to an analysis grid with a cell size of 100 m × 100 m, in order to investigate their mutual influence and the influence on spatial attractiveness.

2.4. Accessibility

For each cell midpoint of the 100 × 100m analysis grid, the accessibility to facilities of basic goods and services was calculated. For some issues (e.g. noise pollution) the Euclidean distance towards facilities makes sense. However, a network-based accessibility analysis outperforms Euclidean distances for most planning issues. Consequently, both methods were applied in order to allow the user to choose either (a) Euclidean distances or (b) network distances to be incorporated as variables in the respective models. For the latter (b), a transition raster with a cell size of 5 × 5 m was created based on the pedestrian, bicycle and road networks, respectively. The walking, biking and car driving distances were calculated as the accumulated travel costs through this transition raster to the respective facilities. In addition (a), distances as the crow flies were calculated using a uniform transition raster resulting in Euclidean distances.

2.5. Used software

The web application for measuring the spatial attractiveness in Herdecke was prepared in ArcGIS for Desktop 10.3.1 (Esri, 1999-2015), uploaded into a web map in ArcGIS Online and integrated into the final web application using the App Builder by Esri Inc. Redlands, CA. The tool for automated data integration was created with Python (V 2.7) and R (V 3.3.1) scripts. Nonetheless, Esri software was already in use within the administration of Herdecke which is also the case for most departments for construction and planning across Germany and Europe. According to requirements of the cooperation partners, the scripts were

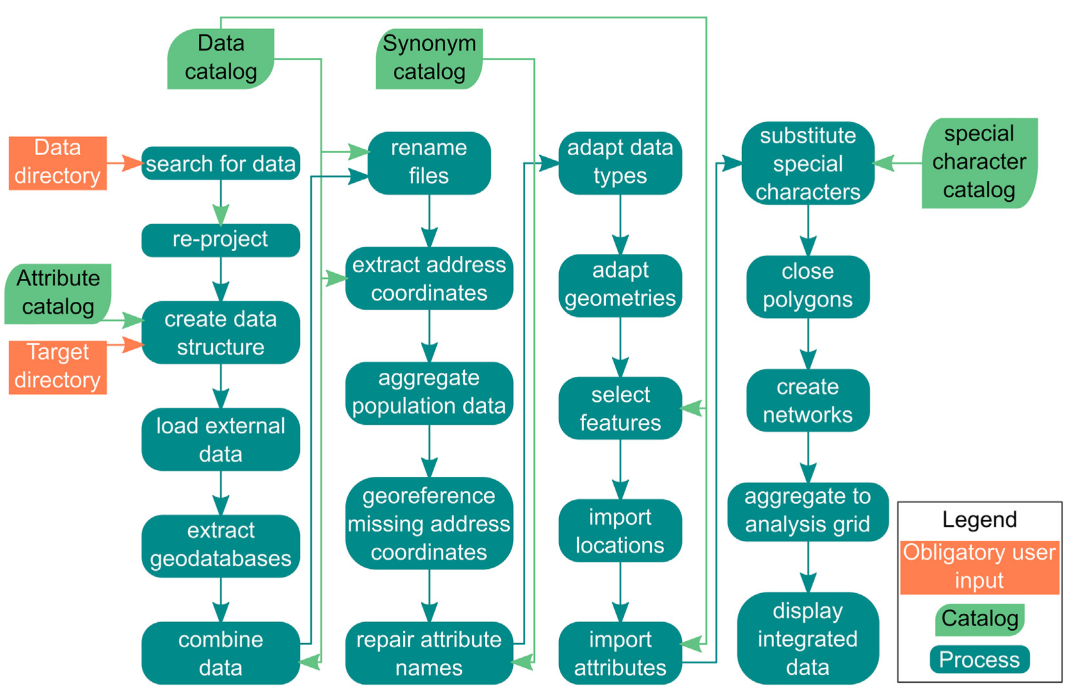

Fig. 1. Schematic diagram of the automated integration of inhomogeneous data sources.

additionally implemented into a tool for ArcGIS. Accessibility calculations were conducted in R using the gDistance package (V 1.1). The gamified simulation and the web-based user interface (described in the following section 3) were created using the Shiny (V 1.0.4) and Leaflet (V 1.1.0) packages for R.

3. Calculation

The spatially implicit (Section 3.2) and explicit rules (Section 3.3), resembling system dynamics and agent-based models (ABM), respectively, were combined into a spatial simulation of urban systems. The following sections set out how the rules for this simulation can be implemented in a straightforward way by users and how a web-based and gamified approach (Section 3.1) makes SimUSys platform for creating simulations intuitive to use and its results easily comprehensible. This is demonstrated with a case study in which the most suitable out of three places for a new location where public events, e.g. concerts, can take place were identified within the city center of Herdecke considering five simulation rules.

3.1. Web-based user interface and gamified simulation

The user interface for the gamified simulation was created as a web-based application which can easily be accessed with a web browser without local installation. As can be seen at the left section in Fig. 2, the automatically integrated data (the position of event locations in this example) was visualized using a tree structured style which is similar to a web GIS. The middle section comprises the map canvas where the integrated data sets and simulation results are displayed with basic GIS functionality, such as zooming, panning, visibility of layers and map legends. The right section in Fig. 2 displays information on the current game score, action points and time steps. The creation of new facilities was simulated in a straightforward way by selecting the respective facility from a drop down menu, clicking on the desired location on the map and confirming or dismissing these steps. The effectiveness of this action was evaluated after the simulation rules were applied (see Sections 3.2, 3.3) in a round-based game design.

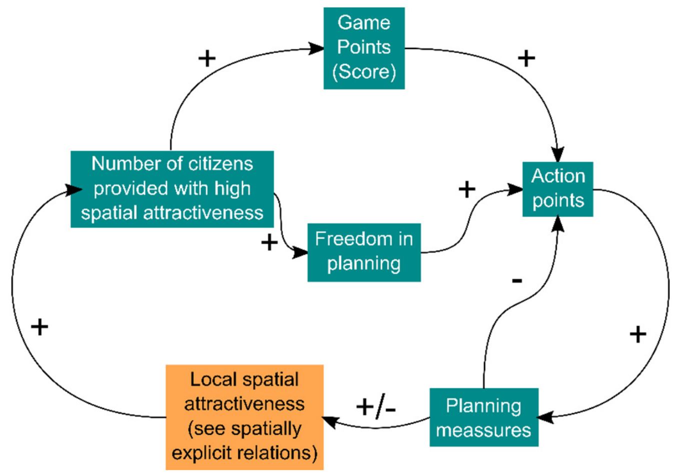

Fig. 3. Schematic diagram of the spatially implicit simulation rules.

3.2. Spatially implicit rules

As can be seen in Fig. 3, high numbers of citizens living in areas with high spatial attractiveness results in a high game score in simulations created with SimUSys. As this increases the freedom of planning due to citizens' contention and approval, this also increases action points which can be used for hypothetical planning measures in alternative strategies. According to the effectiveness of these measures, for instance varying locations for a new facility, this can increase or decrease the local spatial attractiveness which is geographically bound and therefore

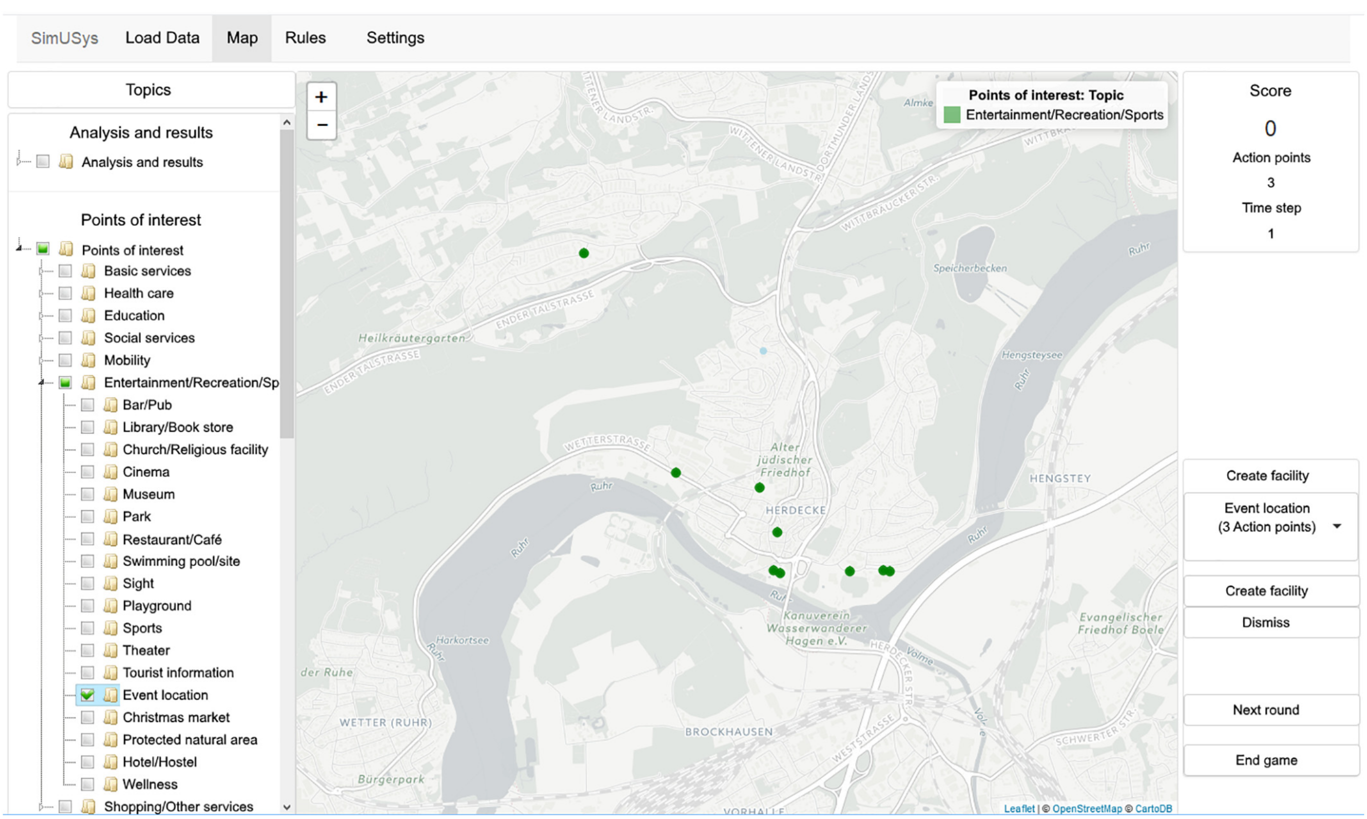

Fig. 2. Web-based SimUSys user interface.

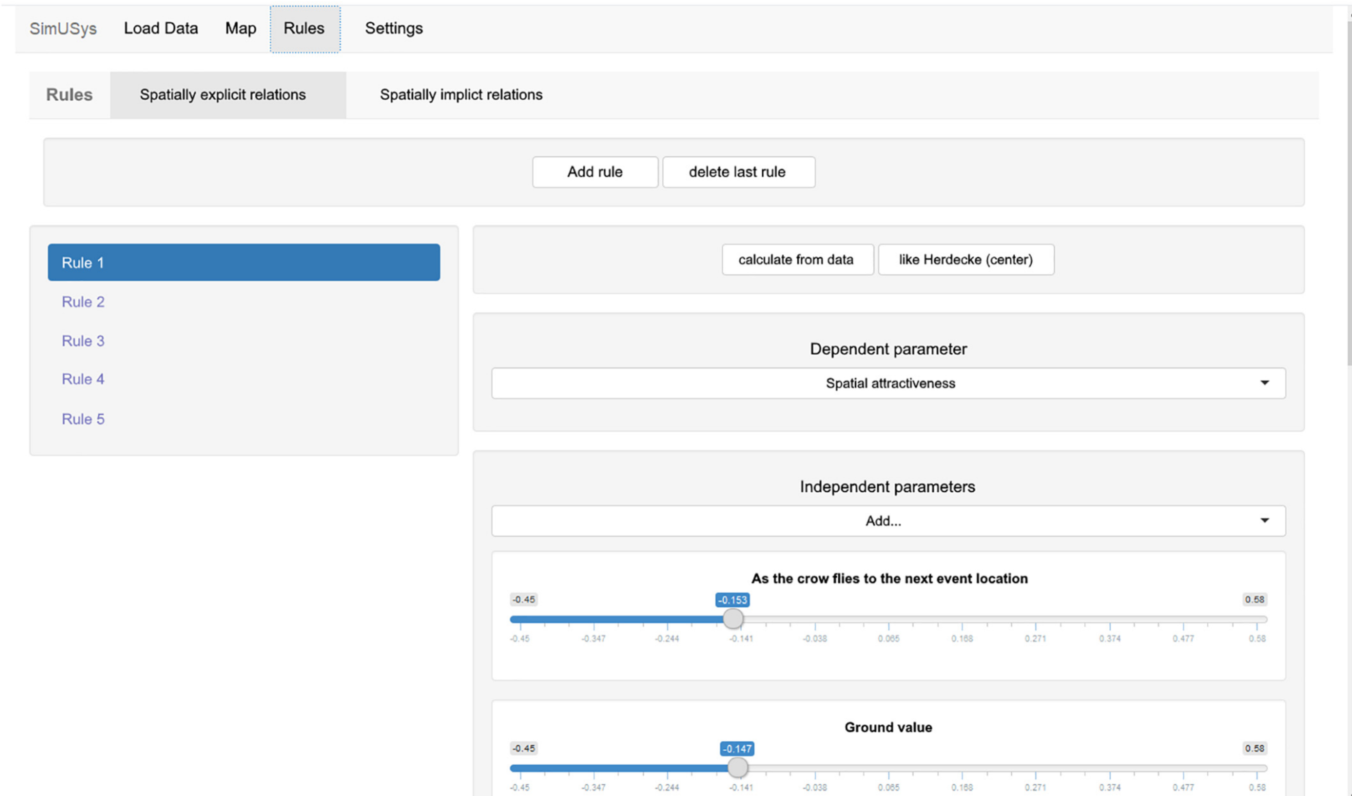

Fig. 4. SimUSys graphical user interface for defining spatially explicit simulation rules. Shown here is the first rule which was set up for the case study in Herdecke considering spatial attractiveness (dependent parameter) and the influencing variables (independent parameters) of which only the first (as the crow flies to the next event location) and second (ground value) are shown.

defined by spatially dependent rules as described in the following section 3.3 on spatially explicit rules.

3.3. Spatially explicit rules

Spatially explicit rules are those which consider local conditions rather than effecting the whole study area in the same way. As can be seen in Fig. 4, spatially explicit rules can easily be implemented into the simulation using the SimUSys graphical user interface. These rules define the behavior and state of the static agents which are the grid cells in the study area. In that respect, these static agents resemble the cells of a CA model (see Section 1). They are not restricted by distinct but rather continuous states on a numeric rational scale. For instance, the numerically measured spatial attractiveness of a grid cell is probabilistically defined by the rules derived from regression models as described below.

The number of rules, the influenced variable within each rule as well as the number of influencing variables can be defined by the user with a few clicks and without any programming knowledge. The degree of each influence can either be defined manually using sliders, set as calculated for the study area of Herdecke (if the simulation is carried out for other study areas) or derived from the data itself using regression analyses.

For the latter, all considered data sets are standardized and the spatial autocorrelation within the data is determined by calculating respective Moran's I values. A geographically weighted multi-variate spatial autoregressive regression analysis (SAR) is performed and the weighted influences of the independent parameters on the dependent parameter is set according to the respective regression coefficients. A PDF report is automatically created for model evaluation and optimization. Various measures of the accuracy and errors are reported to this PDF file, for instance, *p* values for the overall model and the respective independent variables, Nagelkerke pseudo-R^2 values, Akaike Information Criterion (AIC) values, Variation Inflation Factor (VIF) values, cross validation results and sample sizes of valid data points. In addition, diagnostic plots and data visualizations are automatically added to this PDF report.

For the case study in Herdecke, five rules were implemented defining the influences on (1) spatial attractiveness, (2) ground values, i.e. the average price for one square meter land, (3) soil sealing, (4) traffic intensity and (5) noise pollution. The four former rules were derived from the data itself by SAR methods as described above. For this purpose, 60 plausible influencing variables (see Section 2.3 about data integration) were chosen for each model, respectively. In an iterative process, variables were removed from the model using the *p* values of individual variables as benchmarks, the AIC values for model comparison and, in order to control for multicollinearity, a threshold of 15 for the VIF values. In order to demonstrate that rules can also be implemented in cases of insufficient data availability, and based on knowledge of the study area, for instance citizens' concerns or professional expertise, the latter rule, considering noise pollution, was defined manually. It was set to be influenced by the traffic intensity using the sliders for parameter weighting. After defining these spatially explicit rules, they are automatically implemented as probabilistic behavioral rules for the grid cell agents and applied along with the spatially implicit simulation rules (see Section 3.2) without any additional programming.

4. Results

The tool for automated data integration was applied for the study area and resulted in 125 prepared geo-objects from various data sources which were subsumed under the headings of “environment and services”, “networks”, “points of interest” and “planning entities”. These objects provided 275 attributes, including 15 demographic attributes, such as number and age of citizens, 7 infrastructural and environmental attributes, such as traffic intensity and soil sealing. In addition, the walking, bicycle, car and Euclidean distances to 62, 56, 52 and 64 facilities of basic goods and services were calculated, respectively. These geo-objects and their respective attributes were automatically prepared and were ready for defining simulation rules in SimUSys.

For the case study for Herdecke, a survey on spatial attractiveness was carried out using a type of online public participatory GIS and the answers of the survey questions were georeferenced (Mueller et al., 2016b). This survey revealed a positive overall atmosphere with local heterogeneities. In total, 266 places were evaluated throughout the city of which 158 were assessed as "feel good" and 108 as "feel not good" places. The former were mostly located in recreational areas and the city center, whereas the latter were mostly brought forward in the context of construction sites and noise pollution by a highly frequented highway.

In the use case, five rules for the static grid cell agents were implemented defining the weighted influences on (1) spatial attractiveness, (2) ground values, (3) soil sealing, (4) traffic intensity and (5) noise pollution. High and significant Moran's I values of ~ 0.75 ± 0.29 (median ± standard deviation) indicated considerable spatial autocorrelation in the data. This was accounted for during the modeling using SAR methods.

As can be seen in Fig. 5, all regression models were highly significant with p values for the overal models < 0.01. As these models were implemented as probabilistic behavioral rules for the grid cell agents, their accuracy and errors provide information about the performance of the respective agents. The explanatory power, expressed by the Nagelkerke pseudo-R^2 values, were approximately 0.28, 0.76, 0.76 and 0.37 for the spatial attractiveness, ground value, soil sealing and traffic intensity models, respectively. Regression coefficients of the individual parameters were siginificant in all models. All variables, except for two, did show VIF values lower than 2, indicating very low multicollinearity in the data. These two exceptions with VIF values of 13.23 and 13.48 were the Euclidean distance to the next healthcare center and the walking distance to the next bus stop, respectively.

A far Euclidean distance to theaters and event locations and high soil sealing, noise pollution and ground values showed the most negative influence on spatial attractiveness. In contrast, far Euclidean and walking distances to healthcare centers and bus stops showed the most positive influence on spatial attractiveness in the model. These facilities were in parts located in the outskirts of the study area. It is worth noting that the influences which have been determined by the regression analysis should be checked for plausibility and adapted using the sliders as shown in Fig. 4 by the user. Traffic intensity was positively influenced by the traveling distance by car to the next event location. Soil sealing depended negatively on short walking distances to protected natural areas and positively on high ground values. Ground values, in return, were negatively influenced by far distances as the crow flies to parks and bus stops and long traveling distances by car to event locations. As described in Section 3.3, traffic intensity was manually set to exert a positive influence on the noise pollution, demonstrating that rules can also be implemented in SimUSys based on local knowlegde of the study area. For the case study in Herdecke, this was the case as numerous people uttered complaints during the surveys regarding noise pollution by a highly frequented highway. In addition, Fig. 5 indicates the interconnected dependencies within this simple rule set of five defining simulation rules for the grid agents, the model accuracies as well as the influences of a new event location on this system.

Using this set of rules for the grid agents, a serious game was played in order to evaluate three possible places for a new event location in the study area. As can be seen in Fig. 6 (first column), before the simulation was carried out, the spatial attractiveness was highest in the outskirts of the city where natural forest and river areas can be found as well as in parts of the city center itself (in the middle of the study area). Traffic intensity was highest in the southern and northern outskirts where regional roads and a highway are located. The same holds true for noise pollution. Soil sealing as well as ground values were highest in the city center and lowest in the outskirts of Herdecke.

After the new event location was created in the simulation, the traffic intensity and noise pollution decreased and the ground value, soil sealing and spatial attractiveness increased locally (see Fig. 6, columns 2, 3 and 4) as well as in terms of the whole study area (see Table 1) for all three tested sites.

The least effective site was location 1. The creation of a new event location at this place decreased the traffic intensity and noise pollution by −5% and −6% and increased the soil sealing and ground value by +1% and +3%, respectively. This resulted in a + 3% increase of the overall spatial attractiveness which directly affected 69 citizens, who resided within 100 m of Euclidean distance (see Section 2.3 for integration of data by the city's registration office). These were the lowest numbers of the three tested sites and resulted in a game score of −200.

The most effective location for decreasing traffic intensity (−28%) and noise pollution (−39%) was location 3 (Table 1). However, the creation of a new event location at this place increased the soil sealing and ground value by +8% and + 14%, respectively. This resulted in an increase of the overall spatial attractiveness of 9% for a new event location at this place and directly affected 150 people.

The most effective place for increasing the overall spatial attractiveness was location 2 (+10%). Traffic intensity and noise pollution decreased by −26% and − 37%, while soil sealing and the ground value increased by +7% and + 13%, respectively. The creation of a new event location at site 2 directly affected 76 citizens. Nonetheless, although location 2 was most suitable for increasing spatial attractiveness with a game score of 700, location 3 was identified as the most efficient place for a new event location with a game score of 800, as more people were directly affected at this site.

5. Discussion

The presented platform for creating spatial simulation for urban systems (SimUSys) incorporates aspects of system dynamics, ABM and gamification approaches. The spatially implicit rules for this gamified simulation define the motivational affordances, such as game scores and action points, and were implemented as positive and negative systemic feedback loops resembling those of system dynamics models. The spatially explicit rules can be implemented by the user in a straightforward way using the web-based user interface. These spatially explicit rules for the static grid cell agents are in accordance with Batty, Xie, and Sun (1999), who proposed a system modeling framework for GIS-based cellular automata, and constitutes a blend of the cellular automata approach and "spatially explicit, grid-based, immobile" (Reynolds, 1999 on his web page) agents of an ABM. A use case for the city of Herdecke demonstrated how these rules can be derived from the data itself using spatially autoregressive regression analyses. This is in accordance with the tendency in research to incorporate empirical evidence-based data into agent-based models for decision support and policy making (Heracleous, Kolios, Panayiotou, Ellinas, & Polycarpou, 2017; Janssen & Ostrom, 2006; Macal, 2010; Nava Guerrero et al., 2016; Pullin et al., 2009; Pullin & Knight, 2003; Wu et al., 2017).

The tool for automated data integration allowed straightforward access to various data sources which could be used in SimUSys without intensive manual data preparation. This allowed for a combined use of open and official data, of which some data sets could be considered sensitive concerning privacy. In exchange with the cooperating partners in the study area, this was accounted for by the fact that the tool for data integration can be run locally and in an isolated environment in contrast to a web-based service.

The accessibility of local facilities of basic goods and services was evaluated by accumulated travel cost through a transition raster with a cell size of 5 m × 5 m. On the one hand, this comprises an inferior

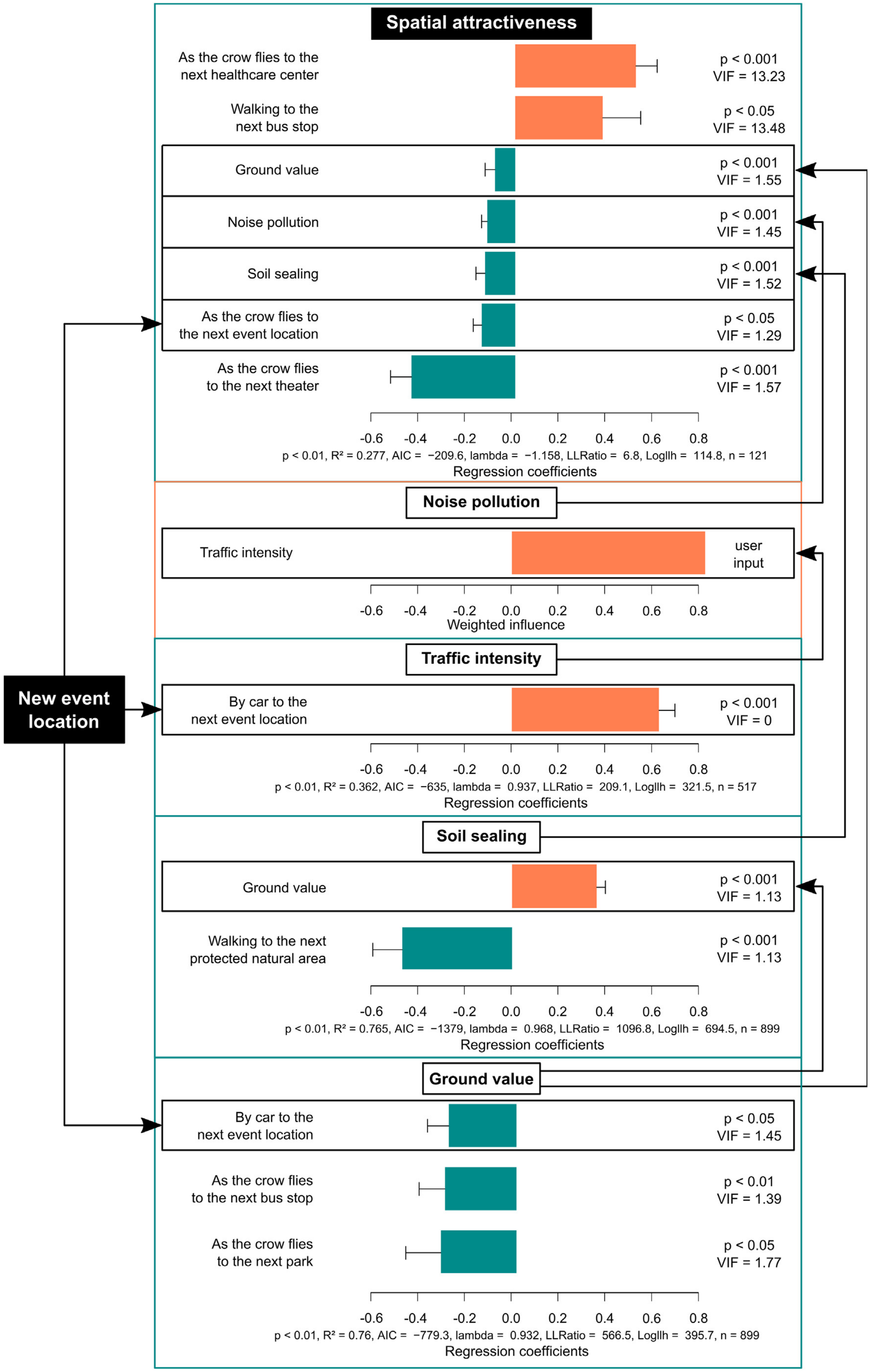

Fig. 5. Weighted influences for five simulation rules derived from spatial autoregressive regression analyes and manual input.

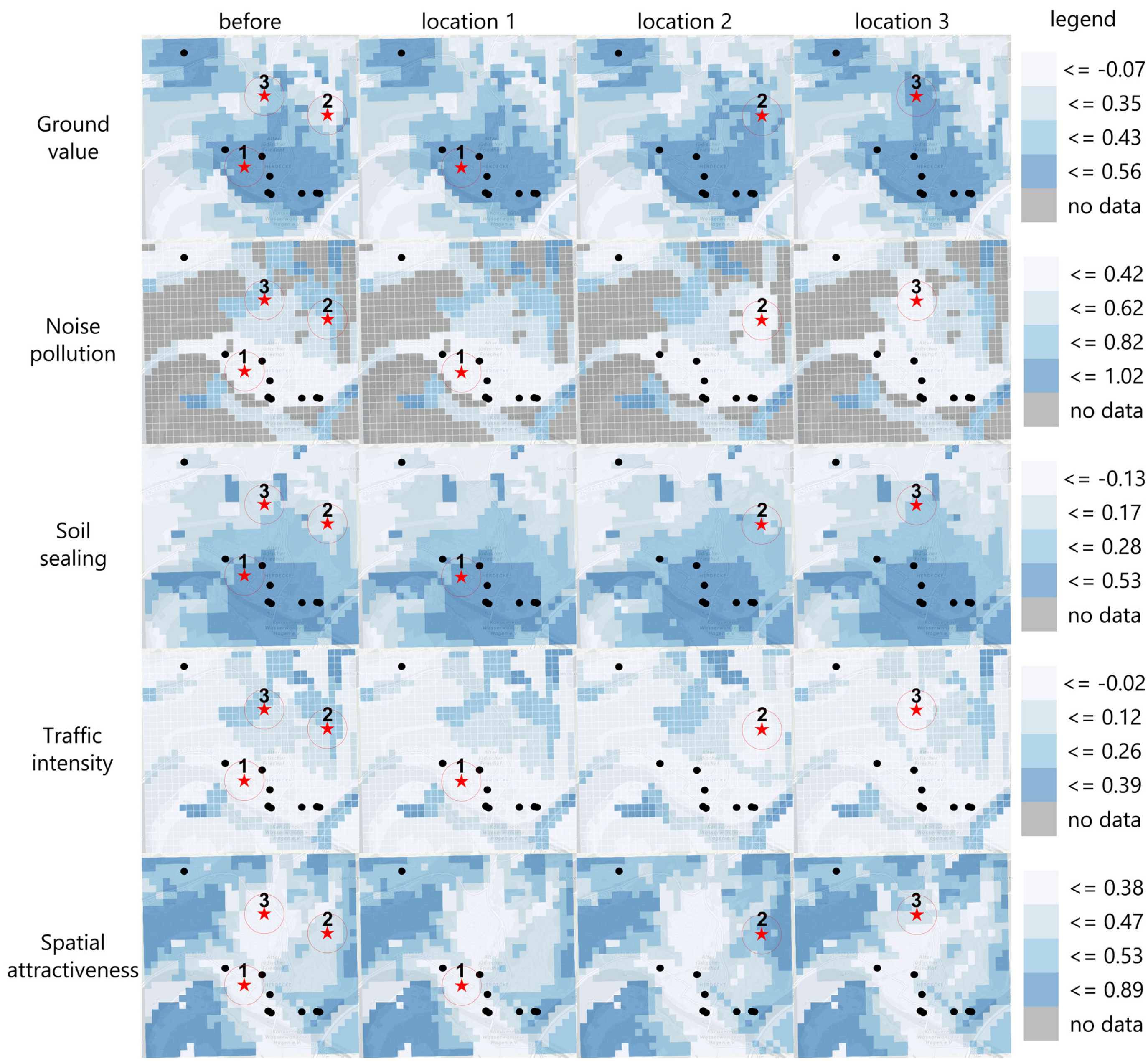

Fig. 6. Overview of the three possible event locations in the study area and the resulting spatial effects. Existing event locations are represented as small black dots. Possible new event locations are represented as small red stars. Legend values constitute proportions of the maximum values before the game was carried out and show values of the respective rows (first legend from the top for "ground value", second legend for "noise pollution", and so forth). Although the new facilities do affect larger areas, their closer vicinities are indicated by circles for reasons of better comparability with the "before" state, in the first column (there are very little changes at location 1, in the second column, and more expressed affects at location 2 and 3, in the third and fourth column). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

approach in terms of accuracy when compared to a network analysis based on a node and edge model. On the other hand, the travel cost analysis outcompetes a network analysis in terms of computational efficiency which allows for real time updates of accessibility values in SimUSys. Furthermore, as accessibility values are individually weighted as part of the spatially explicit rule set for the grid cell agents and not the absolute values themselves are regarded in the simulation, the loss of spatial detail due to the transition raster is considered to be tolerable.

Given the fact that the independent variables in the regression analyses were spatial data sets, multicollinearity was surprisingly low (VIF < 2) for all parameters. The Euclidean distance to healthcare centers and the walking distance to bus stops in the model describing spatial attractiveness were the only exception with VIF values of ~13. Although the predefined threshold of VIF < 15 was not exceeded and the variables in question were therefore not removed from the model, the relatively high VIF values might be avoided by a more diverse data sets in future studies. As expected from the considered spatial data sets, they showed extensive spatial autocorrelation which was accounted for in the spatial autoregressive regression models.

Although all spatial autoregressive models were highly significant, there were considerable differences between the explanatory powers of the respective models and therefore the accuracy of the agents whose behavior was defined by these models. The explanatory power of the regression model which described the influence on ground value was ~ 0.76 (Nagelkerke pseudo-R^2 value) which, given the simplicity of the defined ruleset, is considered to be satisfactorily descriptive. This is little

Table 1
Summary on three possible new event locations in the study area and the resulting overall effects on the rules defining the behavior of the grid agents. Values represent proportions of the maximum value before the simulation was carried out. Desirable and undesirable changes are indicated with green and red backgrounds/in italics, respectively. (Game) points were calculated as shown in Fig. 3.

		Spatial attractiveness	Ground value	Noise pollution	Soil sealing	Traffic intensity
location 1	before	0.39	0.48	0.32	0.43	0.02
	after	0.42	0.51	0.26	0.44	-0.03
	difference	**0.03**	*0.03*	-0.06	*0.01*	-0.05
	population	**69**				
	points	***-200***				
location 2	before	0.49	0.33	0.6	0.25	0.21
	after	0.59	0.46	0.23	0.32	-0.05
	difference	**0.10**	*0.13*	-0.37	*0.07*	-0.26
	population	**76**				
	points	**700**				
location 3	before	0.43	0.35	0.64	0.25	0.24
	after	0.52	0.49	0.25	0.33	-0.04
	difference	**0.09**	*0.14*	-0.39	*0.08*	-0.28
	population	**150**				
	points	**800**				

surprising as ground values are officially assessed and declared using similar regression methods as presented in this study. The pseudo-R^2 value for soil sealing was ~ 0.76 as well, which likewise is considered to be satisfactory. This might be explained by the fact that soil sealing is a phenomenon which usually clusters geographically and occurs with higher intensities in built up areas for which accurate data was available for this analysis. In contrast to that, the explanatory power of the model describing the traffic intensity and spatial attractiveness were rather low (pseudo-R^2 ~ 0.37 and ~0.28 respectively). This might be explained by the simplicity of the models and the fact that additional variables, others than those which were considered, potentially exert strong influences on these measures. Traffic intensity, for instance, might be influenced by factors concerning regional aspects beyond the boundaries of the study area, such as connectivity between larger cities, especially in urban agglomerations such as the Ruhr-Area. Extending the study area in order to depict regional and urban-rural interactions could overcome these drawbacks of the presented methodolgy.

Spatial attractiveness was measured during a web-based survey which was advertised in local media. The explanatory power of the model for spatial attractiveness might be increased by more diverse data. Volunteered Geographic Information (VGI), for instance geotagged tweets on twitter and machine learning techniques for sentiment analyses (Kumar & Sebastian, 2012; Lansley & Longley, 2016; Resch, Summa, Sagl, Zeile, & Exner, 2015; Xu, Wong, & Yang, 2013) could be used as additional data sources in future versions of the simulation platform. By doing so, data collected by VGI methods should be preprocessed and filtered in order to only consider information which was created by citizens. In contrast to the survey described in Section 2.2, this could be challenging as citizens cannot be addressed specifically. An approach to tackle this issue comprises classification methods based on information about user profiles provided as metadata to download tweets using the twitter API.

A further technique which could be applied for data collection includes the so-called *EmoMapping*, which aims to measure the perception of stress at respective places in the city (Beyel, Wilhelm, Mueller, Zeile, & Klein, 2016; Exner, Bergener, Zeile, & Broschart, 2012; Zeile, Exner, Bergner, & Streich, 2013).

Nonetheless, as mentioned above, spatial attractiveness is highly subjective which raises the question whether these quantitative methods are sufficient for measuring this parameter in an appropriate manner. For instance, a cities' neighborhood could be perceived as attractive by individuals due to a combination of parameters which cannot be numerically measured. Rather the personal identification with or social contacts within the area in question influences spatial attractiveness and measuring this requires a qualitative approach which is valuable, yet beyond the scope of this paper. Qualitative methods would therefore contribute a useful input to the described methodology in an interdisciplinary future study. SimUSys provides an interface for results of qualitative methods, as the regression results can be fully adjusted according to knowledge of local peculiarities and individual user preferences before they are implemented as behavioral rules for the grid cell agents. This was demonstrated with the additional fifth rule concerning noise pollution.

The presented SimUSys platform was created for usage in smaller municipalites but can equally be applied to larger cities or rural areas. The rules which define the agents behavior are derived from regression models which in turn are determined by a variable set chosen by the user. This makes the platform highly flexible with respect to its applicability. For these reasons, the upscaling to larger cities is mainly confined by the used data from which the user can choose the influenced and influencing variables. As data is automatically pre-processed, prepared and integrated from various data sources, the data which can be used is considerably broad and could be applied for numerous issues including simulations of larger cities. Another aspect which should be considered for upscaling the framework to larger cities is the computational time which is primarily determined by real time accessibility calculations of facilities of basic goods and services. These calculations are derived from accumulated travel costs through a transition raster. This method reprensents accessbility much more realistically than Euclidean distances (which are also calculated) while being considerably more effective than analyses based on edge and node networks with regard to computational performance. This compromise between accuracy and computational effectiveness makes the SimUSys modeling platform highly efficient and allows for simulations covering larger urban and rural areas with higher data densities.

6. Conclusions and outlook

Within a case study, it was shown how SimUSys could be used in order to identify the most suitable out of three sites for a new event location. The rule set of five spatially explicit and the implicit rules were automatically implemented and applied in this case study and allowed to experience the behavior of this system in a gamified environment.

Envisaged improvements to SimUSys involve the ability to simulate not only the creation of new but also closure of existing facilities and making alterations to the underlying streets and paths, which is the basis for the real time accessibility calculations. Furthermore, the user will be able to add polygons in future versions of SimUSys in order to model alternative zoning plans with respective probabilities for the establishment of new facilities which again might be derived from the data itself using SAR methodologies. This might pose a more realistic model for urban planning, especially for private facilities which are not placed to a specific location by the city administration but rather regulated by zoning plans.

Further improvements include temporarily dynamic population and migration models which should be able to account for different scenarios regarding the dramatic demographic changes in the region. One result of these changes is a severe increase in the absolute number of senior citizens. The proportion of people with reduced personal mobility is much higher than in other age groups. Consequently, mobility barriers will become more important and should be considered in the accessibility calculations in SimUSys (Mueller, Beyel, & Klein, 2017).

Ultimately, it is worth noting that the presented simulation does not constitute an image of the real world, but rather a tool for experiencing system behavior and complexity and, by doing so, providing a starting point for informed discussions.

The presented easy-to-use decision support tool incorporates aspects of system dynamics, ABM and gamification approaches. It automatically integrates data from various sources with data on spatial attractiveness and is suitable for practical application in everyday administrative processes of smaller municipalities and thereby contributes to more targeted, informed and sustainable urban planning.

Glossary

SimUSys Spatial Simulation of Urban Systems
SARS patial Autoregressive Regression
ABM Agent-Based Models
Moran's I Statistical measure for spatial autocorrelation
AIC Akaike Information Criterion, relative measure for model comparison
GUI Graphical User Interface
Spatially implicit geographically not bound/location does not matter
Spatially explicit geographically bound/location matters
VIF Variation Inflation Factor, measure for multicollinearity
n Sample size
(Nagelkerke pseudo-)R^2 Coefficient of determination (or substitute with similar reading), measure for explanatory power
p value Significance value
λ = lambda Maximum likelihood autoregressive coefficient, measure used in model quality evaluation
LLRatio Log likelihood ratio, measure used in model quality evaluation
Logllh Log likelihood, measure used in model quality evaluation
POI Point of interest

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