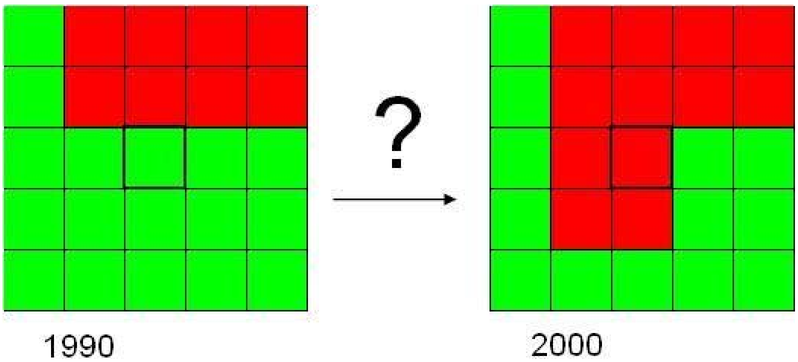
Centre for Geo-Information

Thesis Report GIRS-2009-01

Understanding neighbourhood effects of land use change to improve the calibration procedure of a CA-based land use model

NJH Naus



February 2009

WAGENINGEN UNIVERSITY
WAGENINGEN UR

Understanding neighbourhood relations of land use change to improve the calibration procedure of a CA-based land use model

NJH Naus

Registration number 86 07 02 596 130

Supervisors:

Dr. R. van Lammeren
Ir. H. van Delden

A thesis submitted in partial fulfilment of the degree of Master of Science
at Wageningen University and Research Centre,
The Netherlands.

17-02-2009
Wageningen, the Netherlands

Thesis code number: GRS-80436
Thesis report: GIRS-2009-01
Wageningen University and Research Centre
Laboratory of Geo-Information Science and Remote Sensing

Preface

This report is the result of a period of 6 months full time work to finish the Master study Geo-Information at Wageningen University. A half year filled with extensive calibrations, changing parameters, running models, working with excel, creating maps, analyzing results and writing a report. But on the other hand, this was also a period in which I learned to work 40 hours per week at the same desk behind the same computer; a task that was not always easy for me.

I would like to thank first of all my two supervisors: dr. Ron van Lammeren and ir. Hedwig van Delden for their useful advices, support and tips for further improving my thesis work. The relation with my supervisors was informal and pleasant which I appreciate very much.

During my thesis, I worked at the company called RIKS, which is located in the beautiful city of Maastricht. I would like to thank all my colleagues at RIKS: Bernhard, Edith, Jasper, Jelle, Roel, Patrick and Yu-e (Christy) for the pleasant stay at RIKS, especially during the lunch breaks. And special thanks to my colleague and roommate Jasper who sometimes gave me his advice and shared his opinions during my thesis work. The company RIKS has been a comfortable place to work for me.
Moreover, I would like to thank all my friends for their time to relax besides the thesis work, and colleague GIS students for their interest and questions during the midterm.
Last but not least I would like to thank my parents and my girlfriend for their ongoing support and trust in me.

I hope you will enjoy reading this report.

Nick Naus

Table of contents

Table of figures

Figures:

Tables:

Summary

Land use change models serve a wide variety of purposes. Policy makers can use these models for example to explore impacts and developments of different policy scenarios. Cellular automata (CA) based models can be used for this purpose, because they are spatial, dynamic, highly adaptable, based on rules, simple, but able to handle complex land use change systems. Transition rules in CA-based models describe how cell states change over time and are dependent on the neighbourhood of the cell. The calibration of these transition rules is mainly based on expert knowledge; too little empirical foundation is present. Moreover, trial and error is the mostly used method for calibration which is time consuming and ad-hoc based. More empirical foundation is needed for the calibration of the neighbourhood rules in order to improve the validation of exploring future policy impacts.

The general objective of this research is to get more insight on the neighbourhood relations of land use interactions in the real world and in a CA-based land use change model, and to investigate if it is possible to improve the (semi-automatic) calibration procedure by implementing the knowledge gained in this research in a new calibration run. The following research objectives and question will be dealt with in this research:

1. To determine the land use attraction and repulsion effects present between 1990 and 2000 in both Germany and Spain.
    a. Which attraction and repulsion effects exist and how do they develop over increasing distance?
    b. What are the differences of the attraction and repulsion effects in the two regions?
2. To compare the neighbourhood effects of the land use map and a simulated map of both regions.
    a. What are the differences in the neighbourhood effects of the simulated map and the land use map and can they be explained?
3. To find out whether we can improve the calibration process with the neighbourhood relations found in the real maps.
    a. Can the calibration be improved in both countries with the gained neighbourhood effect knowledge?
    b. Can the results of this research be used in the automation of the calibration procedure?

We have compared three types of (automated) calibration methods suitable for land use change models in this research from literature: a method based on artificial neural networks (ANN), a method based on a mathematically based algorithm and some methods based on spatial metrics. In this research, we will use a type of spatial metric, the enrichment factor, to gain more insight in neighbourhood configurations. The enrichment factor is a measure that indicates whether a certain land use is over or-under represented in the neighbourhood of a cell compared to the average neighbourhood of the total land use map. The neighbourhood configuration is the composition of the neighbourhood of a certain land use cell at varying distances.

Here, we use a tool called Neighbourhood Analyzer to measure the neighbourhood effects of historic data. In this case, we only investigate the cells and their neighbourhoods of which the cell state (land use type) has changed cells between 1990 and 2000 in Spain and Germany. We have used CORINE land cover data from the year 1990 and 2000 to perform this analysis.

First, we have calibrated the Metronamica model (designed and developed by RIKS) for the countries Spain and Germany. We have created attraction and repulsion graphs which

show the logarithm of the enrichment factor on the y-axis and the distance (in cells) from the centre cell on the x-axis. We compared the attraction and repulsion graphs of the calibrations with the graphs of the land use map based on the CORINE Land Cover dataset. Thereafter, we used the differences of these graphs to improve the calibration in a second session. We finally compared the calibrations, the land use map and a randomly created map (RCM map) with cell by cell comparison measures (Kappa statistics) and cluster size based measures (clumpiness index and cluster size frequency graphs).

During the second calibration, significant improvements were being made in the neighbourhood configurations. The clumpiness index values indicated an obvious improvement after the second calibration just as the cluster size frequency graphs. The Kappa values however do not indicate improvements. The neighbourhood configuration is not sensible for small changes made in the neighbourhood rules according to the sensitivity analysis.

We have shown that the use of the enrichment factor during the calibration process is useful in order to improve the neighbourhood configurations and the land uses cluster size and frequency. However, in future research, the differences in attraction and repulsion for the calibrations and the land use maps should also statistically be shown in stead of only visually assessed. Moreover, the neighbourhood configurations of simulated maps depend not only on the transition rules, but also on research area, spatial and temporal resolution, and neighbourhood type. The enrichment factor should be taken into account at every calibration round, also in future automatic calibrations.

1. Introduction

Spatial models can add value in the policy decision making process. These models can be used for multiple reasons. Policy makers use spatial models to explore impacts and developments of policy scenarios, but also to explain relations between land use types and to find uncertainties in their policy directions. An important goal of the usage of these models is to decrease uncertainties in the decision making process or in other words, to improve the exploration and validation of future land use change. A wide variety of land use change models have been set up. An example of a land use change model classification is the one of Briassoulis (2008) which exists of the following classes:

- Statistical and econometric models: statistical models often form a component of larger models. Multiple regression analysis and multivariate techniques are often used. An example of a statistical model based on multiple regression analysis is the Change module in the CLUE model which is used to identify biophysical and socio-economic drivers of land use change (Verburg et al. 2002). Econometrical models are often based on statistical measures to analyse problems involving economic demand and supply. The EMPIRIC model is an econometric model that is used for impact assessment and policy analysis (Hill 1965).
- Spatial interaction models: analyze the flow or movement of people, goods or services based on the attractiveness of a location. In Batten and Boyce (1986) you can find an example of a spatial interaction model.
- Optimization models: models that try to find an optimal solution for a certain set of objectives. Optimization models can be further divided into linear programming models, multi-criteria decision making models, goal programming models etc. An example of an optimization model can be found in Stoorvogel et al. 1995.
- Integrated models: models that link land use changes to two or more components of a spatial system (regions, economic and social components etc.). A wide variety of this kind of models exists, because the term integrated has a broad definition. Examples of integrated simulation models are the CLUE-S model; (Conversion of Land Use and its Effects) a dynamic, spatially explicit model developed for land use change in smaller regions (Verburg et al. 2002) and the cellular automaton based model Environmental Explorer (EE or “Leefomgevingsverkenner” in Dutch) which is an example of a CA-based model used for strategic policy preparations in the Netherlands.
- Others: the majority of land use change models can be placed in one of the above classes. Other models such as ecological models and GIS models (Fisher and Nijkamp, 1993) are placed in this class.

1.1 Determinants of land use change

All land use models mentioned above in the classification are used to model real world land use changes. In order to model spatial dynamics such as land use changes, one has to know which underlying processes trigger these changes. Land use dynamics is a consequence of interactions of human beings and their physical environment which eventually can lead to complex patterns (Verburg et al. 2004). The factors that provoke real land use changes are often called determinants of land use change. A large variety of determinants exist such as biophysical factors (e.g. soil characteristics), socioeconomic factors (e.g. level of income, employment rate), spatial policies (e.g. policies that restrict building in nature areas), but also neighbourhood characteristics of a certain location can influence land use changes (Verburg et al. 2004b). A family looking for a new house to live and to raise their children, takes the direct environment of the house location into account when making a decision. The distance of the new house should be not too far from schools and places to work, but on the other hand it should be not too close to industrial areas and busy roads.

The difficulty of land use change modelling is to simulate as good as possible real world human-human and human-environment interactions.
In this research, the focus will be on these neighbourhood characteristics that can influence land use changes. All determinants in the direct surroundings (neighbourhood) of a location specify the mutual attraction and repulsion effects and are an important determinant of land use change (Hagoort et al. 2008).

1.2 Cellular automata

The modelling of land use involves more and more the use of cellular automata (CA) (Junfeng 2003, Hagoort 2008). Multiple land use change models have been set up based on CA: Batty and Xie 1994, Engelen, Uljee and White 1997, Wu 1998, Torrens and O'Sullivan 2001.
CA are often used for land use modelling, because they are spatial, dynamic, highly adaptable, based on rules, and relatively simple, but nevertheless they are able to handle complex land use change systems (White and Engelen 2000). A standard CA consists of the following basic elements: a grid or raster cell space, different cell states, neighbourhood description of the cells, transition rules and a time scale.
In recent land use models the cell state represents the predominant land use present at this cell at a certain moment such as: industry, forest or built-up area. The neighbourhood of a cell describes which surrounding cells influence the transition of a cell state for a certain cell in the next time step. The cells further away have a smaller influence than cells closer to the centre cell (Tobler 1970). This effect is called distance decay effect (Smith 1976, 1977).The transition rules are the core of the CA and determine if and how the state of each cell in the next time step changes. Time in a CA is discrete with a simultaneous updating of all cell states. The time step is most of the time a matter of convenience and data availability (e.g. 1 year) (White and Engelen 2000, Straatman et al. 2001).

The transition rules in a CA-based model describe how cell states change over time and are strongly dependent on the neighbourhood of the cell. The neighbourhood effect in this research is defined as: the attraction or repulsion effect of surrounding cells which eventually causes a change in cell status (type of land use) of the centre cell.
Unfortunately, the calibration of transition rules of CA-based models is for a large part based on expert knowledge; and too little on empirical research. The calibration of neighbourhood rules is also ad-hoc based by means of trial and error methods which is very time consuming. Furthermore, for supporting and exploring spatial policies, more empirical foundation is needed for the neighbourhood rules in CA-based models. If the link between theory and transition rules becomes more direct, the model outcomes can be better explained using existing land use theories.
In this research, we will use the CA-based Metronamica model for our calibrations. Models such as MOLAND (Monitoring Land Use and Cover Dynamics), which is a spatial planning model to monitor developments of urban and regional areas, (Engelen et al. 2002) and the already mentioned Environmental Explorer are both based on the Metronamica model.

1.3 Attraction and repulsion

Land use conversions are the result of complex interactions between humans, their decisions, the physical environment and other (non-) physical land use change determinants. The neighbourhood of a cell can influence land use conversions in three ways; it can attract a certain land use, it can repulse a certain land use or it does not influence a land use at all. The underlying processes that affect the land use conversions are called centrifugal (repelling) and centripetal (attracting) forces. A large variety of these attraction and repelling forces exist. For the establishment of new residential areas, repelling effects can be: close distance to a dump site or close distance to an airport. Possible attracting effects are: close distance to recreation facilities or close distance to jobs. These examples of site attributes are used in CA-based land use models to model cell transitions. We call this the attraction and repulsion effects at modelling level.

A second meaning of attraction and repulsion is used in researches that analyze neighbourhood effects in CA-based models. We will explain this second definition by means of figure 1. In figure 1, you can see two 3 x 3 raster with the centre cell borders in bold. The green cells represent the land use forest and the red cells represent the land use residential area. The only cell that has changed between 1990 and 2000 is the centre cell. The land use forest has changed into residential area. For both analyses, the neighbourhood of the cell in the initial map is analysed (dashed cells in the initial map). This change of cell status can be analysed in two ways. Is forest repelled by other forest in the initial map (repulsion effect) or is the new residential cell attracted by the other residential cells in the final map (attraction effect)? The type of analyses (attraction or repulsion effects) has to be mentioned in each research in order to be able to interpret the results. Be aware that for this definition, the terms attraction and repulsion only indicate which cells are analysed. In this research, we will analyze the changed cells of the final map only (attraction effect) or in other words: the neighbourhood effects on the newly established residential cell. We will use the enrichment factor to express attraction of repulsion effects. The enrichment factor indicates whether a certain land use in a neighbourhood of a cell is over-or under represented compared to the total land use map.

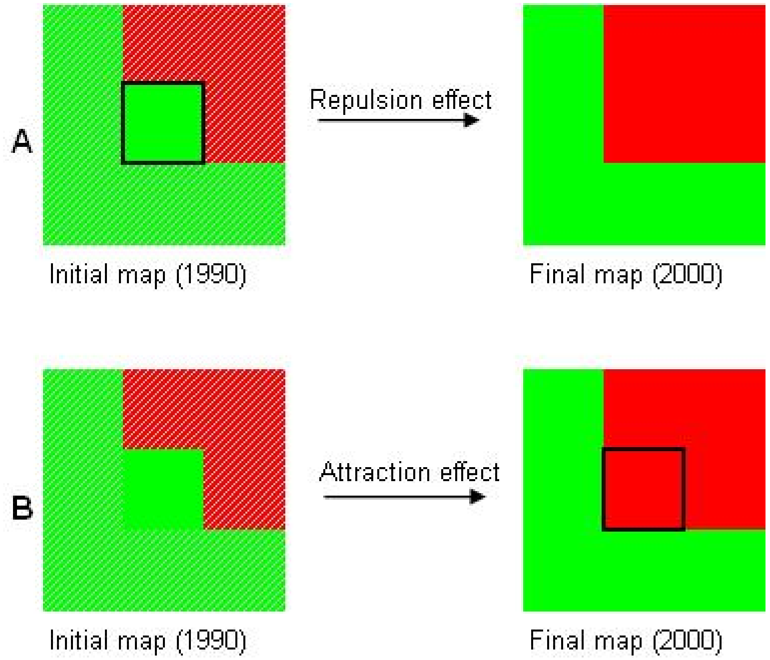


Figure 1: attraction and repulsion effects explained. Two 3 x 3 rasters with the centre cell borders in bold are shown. The green cells represent forest, the red cells represent residential area. The dashed cells in the initial map are the neighbourhood being analysed. A = repulsion effect, B = attraction effect.

1.4 Research objectives

The general objective of this research is to get more insight on the attraction and repulsion effects of land use change in the real world and in a CA-based land use change model, and to investigate if it is possible to improve the calibration procedure by implementing the knowledge gained in this research in a new calibration run. The ultimate goal is an automatic calibration procedure. This research is a step in that direction.

Research objectives and questions:

1. To determine the land use attraction and repulsion effects present between 1990 and 2000 in both Germany and Spain.
    a. Which attraction and repulsion effects exist and how do they develop over increasing distance?
    b. What are the differences of the attraction and repulsion effects in the two regions?
2. To compare the neighbourhood effects of the land use map and a simulated map of both regions.
    a. What are the differences in the neighbourhood effects of the simulated map and the land use map and can they be explained?
3. To find out whether we can improve the calibration process with the neighbourhood relations found in the real maps.
    a. Can the calibration be improved in both countries with the gained neighbourhood effect knowledge?
    b. Can the results of this research be used in the automation of the calibration procedure?

To answer these research questions, we will first calibrate the Metronamica model for two regions by means of a manual calibration. We will then create attraction and repulsion graphs which show the over- and underrepresentations of land uses in the neighbourhood a certain land use at varying distances. The total set of attraction and repulsion graphs is called the neighbourhood configuration of a land use. We will compare the neighbourhood configurations of residential and industrial land use of the calibrated maps with those of the CORINE land use map of 2000. We are going to analyze the differences and we will assess the quality of the calibration by means of different statistics. In a second calibration round, we will then try to improve the results of the first calibration to decrease the differences of the neighbourhood configurations as much as possible. Our ultimate goal is to automate the calibration procedure, but this research is only a step into that direction.

In chapter two, we will describe the methodology, results and discussion of researches that also have dealt with the (automated) calibration of neighbourhood rules. In chapter three, an extensive description of the used methodology is given. In chapter four, we will continue with the presentation of our results and the answers of the research objectives. In chapter 4.1, we will discuss results of the first research objective, in chapter 4.2 the second objective and in chapter 4.3, the third research objective will be dealt with. We then continue with a conclusion and extensive common discussion. For a short description of the terminology used in this research, you can consult the glossary.

2. Calibration of neighbourhood rules

In the previous chapter, we explained that a CA (part of a CA-based land use model) consists of five main elements; (see figure 1) a time scale, a raster cell space, a neighbourhood description, two or more cell states and transition rules. As shown in figure 2, the cell transition rules based on the cell's neighbourhood have to be calibrated so that the model simulates the reality as good as possible. This calibration process is often done manually by experts as described before. However, some researches have made first steps in automating the calibration procedure and finding empirically based transition rules. This research is also a step in the direction of automated calibration and therefore, we first describe three types of researches that also have dealt with the automation of transition rule calibration in paragraph 2.1.

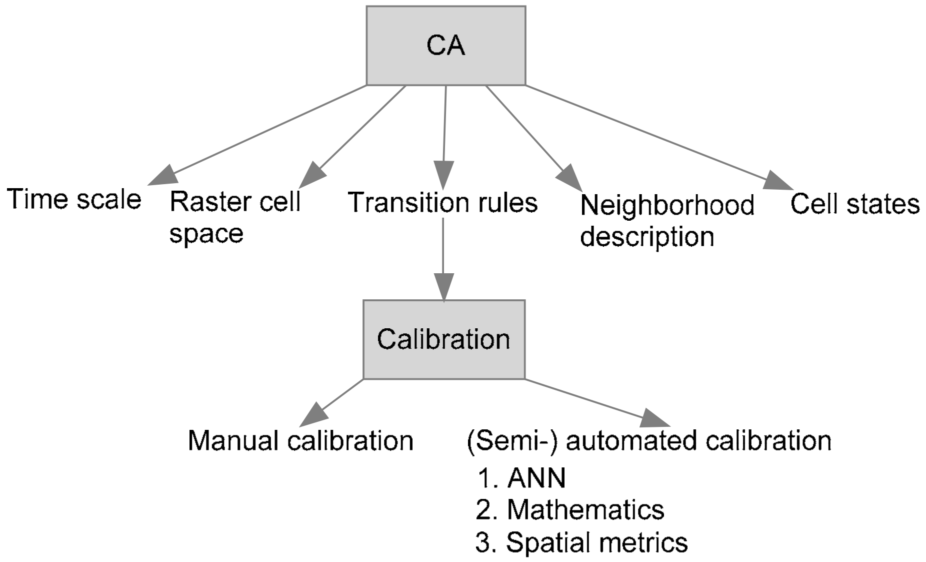


Figure 2: context of automatic calibration methods for CA-based land use change models

Three types of (semi-) automatic calibration methods
Recently, multiple researchers have attempted to find methods to improve the calibration of transition rules. The researchers have tried to find a more automated calibration procedure. Here, we discuss the results of three types of automatic calibration methods suitable for land use change models; a method based on artificial neural networks (ANN), a method based on a mathematical algorithm and some methods based on spatial metrics (see figure 2).

The first example of an automatic calibration procedure uses artificial neural networks (ANN) (Li and Yeh, 2001). ANNs are models inspired on the human brain and consist of an interconnected group of artificial neurons. Each separate neuron is a simple processing element, but multiple neurons together are able to handle complex problems such as land use change modelling. In this research, an ANN-CA based model is used to test this method. Remote sensed data is used to provide empirical data as input for the ANN that calculates transition weights. A GIS is used for defining multiple site attributes for calculating the attractiveness of land uses for all cells. The parameters obtained in this calibration procedure are then used as input for a simulation run. Neural networks calculate development probabilities based on transition weights and site attributes. Only two land use types (developed and non-developed) have been used here. A cell by cell comparison method is used to compare the outcome of this simulation with a logistic regression model based on the same data. It appeared that the ANN-CA based simulation better predicts the exact location of changed cells.

The second method uses mathematics as a basis for an automated calibration procedure. The authors (Straatman et al. 2004) first describe a calibration method for the unconstrained version of a CA model (the number of cells is then only determined by cell dynamics) and thereafter they explain a more complicated method for the constrained version of the model (number of cells is also restricted by demand levels for different activities such as number of jobs).
The Metronamica model calculates transition potentials for every cell and cell state. Normally, this potential is based on neighbourhood factors, suitability, zoning and accessibility (see chapter 3.3), but in this case only the neighbourhood factors are used. The other factors can later be added because only an extra multiplication is needed to calculate cell potentials (Straatman et al. 2004)
First, an initial map of weight factors is chosen and the mathematical model compares the differences of the simulated output and the desired output. Two types of errors can occur which cause the differences in land use allocation between the calibrated output and the desired output. Assume that the land use in the calibrated map is forest, but in the desired map residential. The first possible type of error is that the potential of forest in that particular cell is too high and should be lowered. The second possible type of error is that the potential of residential is indeed higher than forest in that cell, but all residential cells have already been allocated. With this knowledge, the weight factors are adapted for the neighbourhoods with the largest errors. The total error is calculated (number of cells that are in the wrong state) and the weight set with the lowest total error is chosen. The procedure is repeated for this new set of weights until the total error is close to zero. It is possible that the total error is larger in a run compared to the previous run. In this case, the process has entered a local minimum and the mathematical model automatically returns to a previous stage where the potential difference is larger. Then, the process is continued.
Most attempts for this method resulted in perfect calibration for the unconstrained model. The constrained model can also be calibrated, but a minimum amount of data is needed for this which has to be investigated further (Straatman et al. 2004).

The third method involves the usage of spatial metrics to gain more knowledge on an empirically based method to analyze neighbourhood characteristics and how they can be used in an (automated) calibration procedure.
Spatial metrics are used to quantify spatial patterns and are mostly used in landscape ecology. Here, the enrichment factor is used which indicates whether a certain land use in a neighbourhood of a cell is over-or under represented compared to the total land use map. Three researchers have been studying the usage of the enrichment factor.
The first researcher (Verburg et al. 2004) divides the Netherlands in a high and low part and then calculates enrichment factors for these parts and for every province separately to analyze the region-dependent variability. He finds that the division in a high and low part can improve calibration results, because apparently biophysical factors used to have an influence on land use allocation. The separation into provinces did not give any significant improvements. Furthermore, enrichment factors are calculated for a land use map of 1989 and they are calculated for all 1989 cells at which land use has been changed between 1989 and 1996. A large similarity between neighbourhood characteristics for the newly developed locations and the existing locations in 1989 is found.
Finally, a logistic regression model has been set up that relates the location of changed land use with the enrichment factors for the neighbourhood. The goodness of fit of this model has been assessed with the Relative Operating Characteristic (ROC) value. To calculate the ROC value, a curve is plotted with on the x-axis the percentage of cells that is categorized as non-changed cell in reality, but modelled as changed cell, and on the y-axis the percentage of cells that is modelled as changed cell, and has also changed in reality. The ROC statistic is calculated as the area beneath this curve and ranges from 0.5 (completely random) to 1 (perfect discrimination). Direct neighbours and cells at distance between 1500 and 2100 meter give the highest explanation. The logistic model has a high ROC value of 0.91; most conversions took place at locations with a high conversion

probability. The author pleads that not only neighbourhood factors determine land use change, but also important factors such as policy measures, soil suitability, tenure status etc. The findings in this research cannot be used directly as input for CA-based models, because the neighbourhood relations found are calculated during a 7-year period. The neighbourhood relations in the CA land use models are calculated every year during the simulation. Due to the non-linearity of the relations, they cannot easily be transformed.

The second researcher (Hagoort et al. 2008) wants to investigate the neighbourhood effects that influence land use change processes, but also how the strength of these neighbourhood effects is shaped over distance. Furthermore, he wants to find out if neighbourhood influences can explain past land use changes and simulate future changes. He used a combination of extensive literature research, expert interviews and the enrichment factor to formulate neighbourhood rules. The neighbourhood rules used for a general simulation of the Netherlands were calculated using the expert interviews and the literature study.
The enrichment factor is thereafter used to improve the rules and to simulate four urban areas in the Netherlands. The performance of these simulations is assessed with a cell by cell comparison method and compared with a randomly created land use map. The CA model performs better than the randomly created map, but the separation in regions and time periods improves the model results even more.
Also in this research, regional and temporal calibrations appeared to improve calibration results compared to a general model for whole of the Netherlands.

The third author (Hansen, 2008) wants to “quantify and analyze neighbourhood characteristics and use this information for cell-based land use modelling”. In this research, again the enrichment factor is used to calculate under or overrepresentation of land uses. In contrast to Verburg, that uses a seven year time period, Hansen wants to use a yearly interval dataset. He uses a building and housing register with information on building use and year of construction to create a yearly dataset of urban land use classes. Together with nature type registrations and the CORINE dataset, he created land use maps for every year from 1990 to 2000. He creates influence graphs that show the attraction and repulsion of land use types mutually. These graphs are based on the enrichment factor and he compares the outcomes of his yearly based analysis and the outcomes of a 10-year based analysis. A yearly based analysis gains more realistic graphs, but the differences are small. A next step will be the implementation of the neighbourhood rules in a simulation run, but this has not been done yet.

The above mentioned methods are all different approaches for the same end goal; an automation of the calibration procedure for CA-based land use change model. However, these results are only a first step. The first two methods have used a more mathematical procedure to optimize transition weights, whereas the last method uses more spatial metrics. The main disadvantage of the first two methods is the absence of a clear knowledge of the underlying calibration process and the relations involved. Direct land use relations and interactions are not used in these methods. If we use the enrichment factor however, we directly measure the influence of land uses mutually. These results can be used to improve our knowledge about neighbourhood relations.

In table 1, an extensive overview of all methods described above is given which includes the method, results, advantages and disadvantage, and the author’s discussion of the method. Also, the spatial and temporal extent and resolution is shown where possible.

In this research, we want to elaborate on the findings above. We want to investigate a more empirically based method and therefore will use the enrichment factor of Verburg which directly measures attraction and repulsion of land use from land use maps.

We will gain more insight in attraction and repulsion effects of the neighbourhood of land use cells. The terms attraction and repulsion can however have different meanings as explained in paragraph 1.3. We will now shortly indicate the usage of these terms in the above described researches.

In the ANN-CA based method, the authors (Li and Yeh, 2001) have mentioned the term attractiveness which has been calculated by means of seven site attributes during the calibration procedure. These site attributes are distance to urban area, distance to suburban area, distance to closest road, expressway and railway, amount of development in a 7x7 cell neighbourhood and agricultural suitability. These site attributes are used as input for the calibration procedure.

In the mathematical approach, Straatman et al. (2004) use weight factors to value the attraction and repulsion effects. These effects are only values and are not considered as site attributes.

The third method involves both definitions of the terms attraction and repulsion as mentioned before. Hagoort (2008) creates attraction and repulsion graphs based on expert interviews and literature study. He adapts these graphs for several regions, based on the over-and under representation of land uses in these regions compared to the countries average values. The enrichment factor has been used to calculate these over-and under representations for one single (static) year.
Both Verburg et al. (2004) and Hansen (2008) use the changed cells in the new land use map to determine neighbourhood characteristics, which is the map of 2000 in our case, based on the neighbourhood of the initial map (1990 in our case), but they do not motivate their choice. In other words, they investigate the attraction of the new land use based on the neighbourhood of the initial land use map.

In this research, as mentioned before, we will use the ‘attraction’ approach, because we believe that a change in land use nowadays is more influenced by the attractive elements of the new location.

Authors	Model used for calibration	Calibration method	Results	Advantages	Disadvantages	Authors discussion	Spatial extent and resolution	Temporal extent and resolution
Li and Yeh (2000).	Integrated model based on an artificial neural network (ANN) and a Cellular Automaton (CA).	Optimal weights are calculated with ANN and used as input for simulation. GIS defines site attributes.	ANN-CA model calibration accuracy is higher than a logistic regression model for the same data.	1. Parameters automatically calibrated. 2. Good simulation results.	1. Underlying processes of land use change unknown. .	Further study is needed for simulation with multiple competing land uses. Further studies needed to simulate planned development in stead of actual development.	Spatial extent: 2465 km^2. TM images (30 x 30 m) resampled to 50 x 50 m resolution.	Temporal extent: two maps 1988 and 1993, temporal resolution: unknown.
Straatman et al. (2004).	Integrated CA model Environmental Explorer (EE).	EE calculates transition potentials for every cell and cell state. Weight factors are chosen and adapted until error reaches zero.	Unconstrained model: most attempts resulted in perfect calibration. Constrained model: calibration is possible; however minimum data set size is needed.	1. First step mathematically based automatic calibration. 2. Method compatible with zoning, suitability and accessibility.	1. Not yet suitable for larger datasets. 2. Path dependency → no unique solutions. 3. Relations not causal.	Path dependency sometimes problematic. Which unique solution is best? What if data is not perfect which in reality is always the case?	Two maps are compared; each consists of a raster with 100 cells (10 x 10 m).	Unknown
Verburg et al. (2004).	Integrated CA model Environmental Explorer (EE).	EE is used for simulations. Enrichment factor is used to adjust calibrations and to create logistic regression model.	Regional and scale variability effects exist. Large similarity between neighbourhood characteristics of 1989 and difference of 1989 and 1996. Enrichment factors have high explanatory power (ROC).	1. Method empirically based.	1. Expert knowledge needed to choose input variables for logistic model. 2. Neighbourhood relations calculated for a 7-year period. CA-model uses 1-year time step. 3. Results not directly usable, because neighbourhood relations are not all causal related.	Neighbourhood not the only factor that influences land use. Method better applicable if 1-yearly land use data becomes available. In the near future, remote sensed data makes this possible. Now rectangular neighbourhood used → circular would be better.	Spatial extent: the Netherlands (41.528 km^2). Data aggregated to a 500 x 500 m resolution.	Temporal extent: two maps 1989 and 1996, temporal resolution: model step is 1 year.

Authors	Model used for calibration	Calibration method	Results	Advantages	Disadvantages	Authors discussion	Spatial extent and resolution	Temporal extent and resolution
Hagoort et al. (2008).	Integrated CA model Environmental Explorer (EE).	Calibration based on literature research, expert interviews and spatial metrics (enrichment factor).	General rules (whole Netherlands) performed better than randomly created model. Regional and temporal adaptations improved calibration results.	Method includes empirical and theoretical foundation.	How to adapt neighbourhood rules is not explained. Method involving expert interviews, literature study and spatial metrics very time intensive.	Higher level of validity and improved practical usability needed for planning support models.	Spatial extent: 41.528 km² Spatial resolution: raster maps with 100 m resolution.	1986-1993, 1993-2000 and future simulation has been run for 2000-2014. Temporal resolution: 1 year
Hansen (2008)	LUCIA modelling framework	Enrichment factors calculated for each year and used to make attraction/repulsion graphs.	Results compared with method of Verburg (enrichment factor only for 7-year period). Results with 1-year interval are better.	First step in the direction of a yearly based neighbourhood analysis.	Only urban land use classes were available at a yearly base, other classes not. Comparison with Verburgs method only visibly assessed, not statistically. No simulation have been run and compared.	Simulations and validations still to be done. Same research for a metropolitan area started.	Spatial extent: region of Northern Jutland (± 26098 km²). Spatial resolution: raster map with 100 m resolution is used.	Temporal extent: 1990-2000 (10 years). Spatial resolution: 1 year.

Table 1: overview researches involving neighbourhood analysis for CA-based land use change models

3. Methodology

The methodology section consists of four paragraphs. In paragraph 3.1, we will describe the research area and the data that we used for the analyses. In paragraph 3.2, we will describe the neighbourhood analyser which is the tool that we used for the analyses of neighbourhood relations. In paragraph 3.3, Metronamica, the model that we will use for the calibrations is shortly dealt with. Finally, in paragraph 3.4, all research steps, led by the objectives and research questions, are extensively described.

3.1 Research area and data

The research has been conducted with data from two countries: Spain (36°- 44° N, 9° W- 3° E) and Germany (47°-55° N, 6°-15° E). The choice of these two countries is not without reasons. First of all, we want to compare two regions with approximately the same size, but with some differences in land use. Therefore, we have chosen for the Mediterranean country Spain and the more temperate country Germany. Moreover, we want to use the free CORINE land cover data set, so our choice is restricted to EU member countries. Another reason is the difference in the data gathering for each country. We have looked for two countries that have almost similar data gathering periods for the CORINE 1990 and CORINE 2000 map. In case of Germany, the data has been gathered from 1987-1991 for the 1990 map and from 1999-2001 for the 2000 map. Spain has gathered data from 1984-1990 for the 1990 map and from 1999-2002 for the 2000 map. If we take all factors mentioned above together into consideration, the countries Spain and Germany are the best choice. Moreover, RIKS bv has already set-up another application for Spain, so in the future comparison is possible. In table 2 a small overview is given of the size of two countries.

Table 2: overview of research area sizes

Country	Total area	Number of columns	Number of rows
Spain	504.030 km²	4328	4152
Germany	357.021 km²	2600	3504

The CORINE land cover data from 1990 and 2000 are used to perform the neighbourhood analysis. A data set with a resolution of 250 and 100 meter is available for these countries. We will use the maps with a resolution of 250 meters mainly because the calculation time will not be too long. The CORINE data set is freely available and some other models set up by RIKS also use this data. The main advantage of this data set is the high consistency in classification. The data set has been assessed with an ISO-19113 and ISO-19114 quality label with good outcomes (EEA 2008).

The CORINE land cover maps use a classification with 44 different classes. We have reclassified the maps into ten categories: natural vegetation, residential, forest, agricultural, industrial and commercial units, recreation, wetlands, mineral extraction and dump sites, infrastructures (including airports and harbours) and water. This reclassification has two main aims: the number of classes will be reduced so the number of neighbourhood relations will not be too large for the analysis and the classification will be similar with other applications of RIKS which simplifies the usage of the findings in different models.

3.2 Neighbourhood Analyzer

The tool we will use to calculate the neighbourhood effects is called Neighbourhood Analyzer and has been created by RIKS. The tool has multiple settings which can be adapted by the

user. The tool has two obligatory inputs: the region map and the initial map. The region map is a binary map on which is indicated what part of the initial map has to be investigated. It consists of 0's (outside interest area) and 1's (interest area). The initial map is the first map in chronological order you want to analyze (in this case CORINE 1990). If you want to analyze the neighbourhood relations at one single moment in time (see Verburg 2004b), you only need these two maps. We are, on the contrary, interested in neighbourhood relations of the *changed* land uses of cells in a certain time period. Therefore, we need the third input option 'Final map' which is a map with land use data gathered later than the initial map (in this case CORINE 2000).
Furthermore, we will use a neighbourhood radius up to 16 cells to investigate the effect of the neighbourhood relations up to a distance of 16 cells. The radius will be calculated in circles around the centre of the cell. For a radius of 5, the cells present between 4.5 and 5.5 from the centre cell are taken into account.

With the aid of this tool, three types of analyses are possible. We can analyse neighbourhood relations in the initial or final map only (the relations of neighbouring cells of one single year will be assessed with this option), but we can also investigate the repelling and attraction effect of changed cells between 1990 and 2000. The differences of these options have already been explained in chapter 2.2. Finally, an analysis of only unchanged cells is possible.

The output of the tool is an excel file with separate tables for each land use present in the initial and final map. For each land use type separately, the amount of cells that changed from 1990 to 2000 into this particular land use at different distances is calculated. We look into the table of the land use 'forest' for example. At distance = 0 we can see the number of all cells in the raster that have changed from all other land uses present in 1990 except forest to land use forest in 2000. At every integer distance larger than 0 (maximum distance in our case = 16), the quantity of cells in the neighbourhood of cells that have been changed into forest can be seen.

The second step is to calculate the relative attraction of all land uses at a certain land use. We use a formula which resembles the enrichment factor of Verburg et al. (2004). The enrichment factor is a measure that indicates whether a certain land use is over or-under represented in the neighbourhood of a cell compared to the average neighbourhood of the total land use map. The main difference is however, that we only look at cells of which the land use type has been changed between 1990 and 2000. Equation 1 will be used to calculate the enrichment factor:

$$\overline{F}_{k,l,d} = \frac{n_{k,l,d} / n_k}{N_{k,d} / N} \qquad \text{Equation 1}$$

Where:

$F_{k,l,d}$ = the enrichment of a land use type l to land use k at a neighbourhood with a distance d

$n_{k,l,d}$ = the number of cells of land use type l in the neighbourhood d which have been changed from 1990 to 2000 into land use type k

n_k = the total number of cells which have been changed into land use type k between 1990 and 2000

$N_{k,d}$ = the number of cells in the neighbourhood with distance d of all cells in the land use map raster with land use type k

N = all cells in the raster

The calculations will be performed for all land uses present in the research area. The enrichment factor indicates an over-or underrepresentation of cells in a neighbourhood compared to the total amount of cells.
If for example, the neighbouring cells for the land use forest at distance 3 consist of 50% agricultural land and the fraction of all cells in a country which have agriculture as neighbour at distance 3 equals 25%, the enrichment factor of agriculture at forest at distance 3 is 2.

The final step is to transform all relative attraction values with a logarithmic function in order to get attraction and repulsion on the same scale. After this transformation, values larger than 0 indicate an attraction effect, values smaller than 0 indicate a repulsion effect and a value of 0 indicates that the land uses do not influence each other. Eventually, graphs can be created with attraction and repulsion values of every land use interaction.

In this research, we only will investigate the attracting effect of surrounding cells (see figure 2). We will only investigate cells (and their neighbourhood) that have *changed* between 1990 and 2000. If we investigate the neighbourhood relations of the cells that have actually changed, we are able to see which cells in the neighbourhood have encouraged and discouraged the land use change.

As input files, we will use the CORINE land cover map 1990 (initial map) and 2000 map (final map). The region maps will consist of a grid map indicating the research area which is in this case Spain and Germany.

In this research it is unfortunately not possible to test significance of the found land use interactions, because of the complexity involved and a lack of time to program this in the Neighbourhood Analyzer.

3.3 Metronamica model

The model we will calibrate to investigate the neighbourhood rules, is called Metronamica and has been developed and designed by RIKS. This model is a constrained cellular automaton which means that the cell status in this model is not only determined by cellular dynamics, but also by exogenous factors. The Metronamica model consists of a CA based land use model (micro level) and a regionalized economic and demographic model (macro level). At the national level, the model uses growth scenarios for the global population, economic activities and the expansion of natural land uses as global trend lines. At the regional scale, a gravity model calculates the demands for land use and activities. The growth figures calculated at national level are divided per region, taken regional inequalities into account. In this case, we have used a simplified version of the regional model. We use the CORINE maps of 1990 and 2000 to calculate land use cell demands for each region for the initial and final year.
Finally, at local level the land use constrained CA model calculates the allocation of people and economic activities based on the following transition potential:

$$P_j = vA_jS_jZ_jN_j \qquad \text{Equation 2}$$

Where:

P_j = the potential of the cell for land use j

v = a scalable random perturbation term (to take unpredictable human decisions into account)
A_j = the accessibility of the cell to the nearest road network
S_j = the intrinsic suitability of the cell for land use j
Z_j = the zoning status of the cell for land use j
N_j = the neighbourhood effect on the cell for land use $_j$ (White et al. 2000).

The neighbourhood effect is calculated at a radius of eight cells. With the neighbourhood analyser (chapter 3.2), we will calculate neighbourhood effects up to a distance of 16 cells however to see what the magnitude of the effects is at these larger distances. Until regional cell demands are satisfied, cells will change to the land use type with the highest transition potential.
In the model, the classes residential, forest, agricultural, industrial and commercial units, and recreation are used as function classes. These classes will be actively allocated by the model. Wetlands, mineral extraction and dump sites, infrastructures and water are feature classes and their number of cells is fixed. They only can change by an intervention outside the CA dynamics. Finally, the class natural vegetation is a vacant class and this allocation is a residual of the dynamics of the function and features classes. We will only investigate the neighbourhood relations of the five function classes, because these classes will actively be allocated by the model. The influence of all function classes on every single function class will be determined.

3.4 Research steps

In this paragraph, we will describe the research steps for every research question separately. A visual representation of the research steps can be found in figure 3. Before we started this research, we have studied literature to increase our understandings of the problem definition (step 1). In step 2, we have created all data needed to perform the analysis. In step 3, we performed the first calibration round and we assessed the outcomes with some statistics. In step 4, 5 and 6, we have analysed the neighbourhood relations with the attraction and repulsion graphs. In step 7, we have performed the second calibration round to improve the calibration results. In step 8, we have analysed the sensitivity of the enrichment factor if we change transition rules systematically. Finally, in step 9, we have discussed all results and make some recommendations.

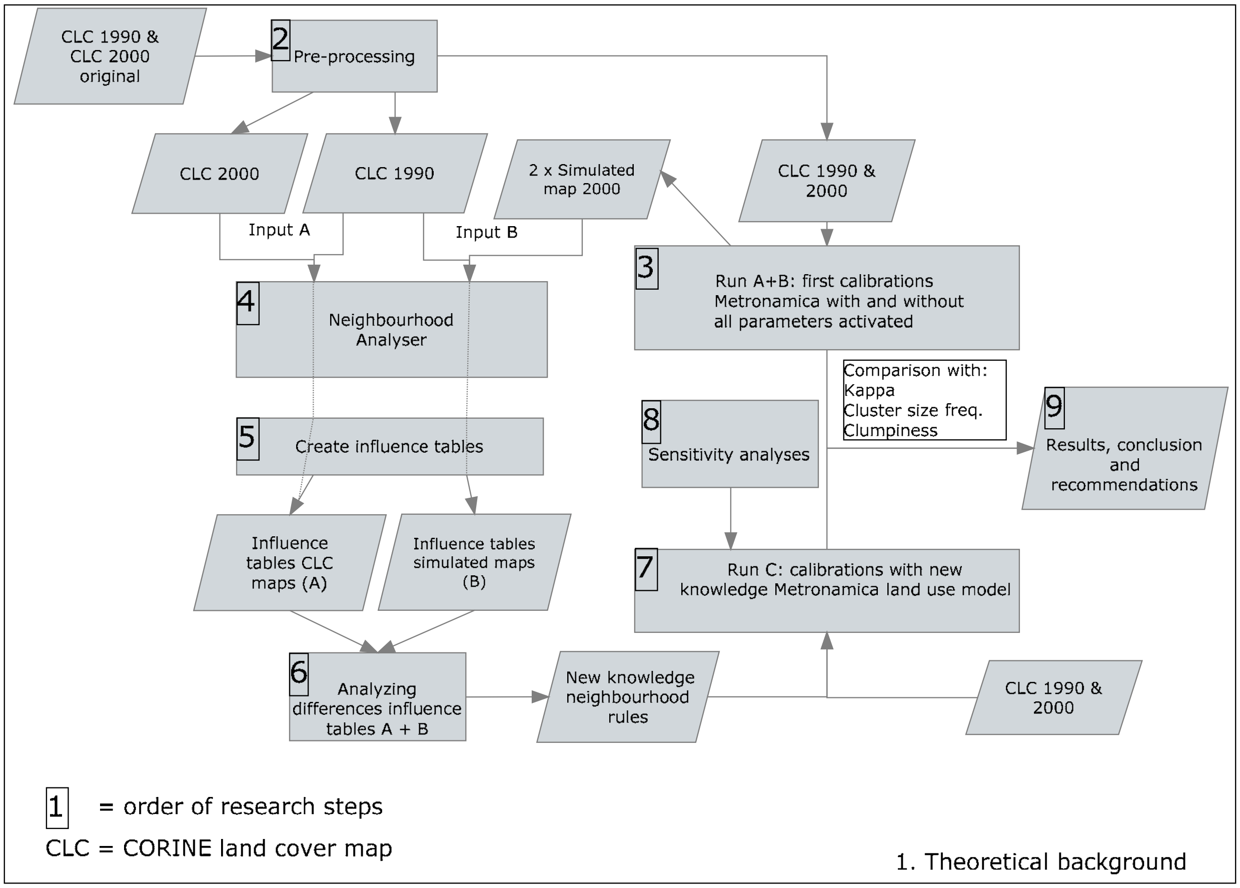


Figure 3: flowchart of research steps

3.4.1 Step 1: literature study

The first step involves a literature study on the subject to increase the theoretical background knowledge. The underlying problem definition and other researchers work involving the calibration of neighbourhood rules have been studied. In chapter two, we have outlined the results of this study.

3.4.2 Step 2: data pre-processing

The second step is the pre-processing of the CORINE data. The data has to be reclassified into ten categories corresponding with other Metronamica applications (see previous chapter) in order to make data processing and result comparison easier. Furthermore the Metronamica macro model has to be filled with cell demands as explained before. Also, multiple maps have to be created that serve as input for the neighbourhood Analyzer and the Metronamica model (see chapter 3.2 and 3.3). The Neighbourhood Analyzer needs an initial, a final and a region map for both countries as input. In order to calibrate our model, we need a zoning map, a transportation map and suitability maps of all function land use classes for both countries. In table 3, an overview is given for the different map types.

Table 3: overview map types used in the analysis

Type of map	Created in:	Input for:	Map shows:	Based on:
Initial map	ArcMap	Neighbourhood Analyzer	Land cover classes present in 1990 in the research area.	CORINE
Final map	ArcMap	Neighbourhood Analyzer	Land cover classes present in 2000 in the research area.	CORINE
Region map	ArcMap	Neighbourhood Analyzer	Research area indicated by 1 and out of modelling area indicated by 0. Only the neighbourhood of cells with a value 1 will be used for the calculations.	CORINE
Region map	ArcMap	Metronamica	Every region in a country has an unique value	CORINE
Suitability map	ArcMap	Metronamica	Suitability ranging from 1 (very suitable) to 0 (not suitable) for each function land use class.	LUMOCAP project (RIKS, 2008)
Transportation network map	ArcMap	Metronamica	Main road network for the calculation of the accessibility.	LUMOCAP project (RIKS, 2008)
Zoning map	ArcMap	Metronamica	Zones where certain land use development is not allowed, per land use	Natura 2000

3.4.2.1 Initial and Final maps

The CORINE land cover data set consists of 44 different land cover categories which we have reclassified into 11 classes (natural vegetation, residential areas, forest, agricultural areas, industrial and commercial units, recreation, wetlands, mineral extraction and dumpsites, infrastructure (including airports and harbours), and water). The function Reclassify in ArcMap has been used for this purpose. The exact reclassification schema can be found in the Appendix I.

After the reclassification, a separate clip for the countries Spain and Germany has been created. The four outer x and y coordinates are used to create this clip. Furthermore, we added a zone of 16 cells (4 km) around this box, because we will analyze the neighbourhood of the cells at a radius of 16 cells. If we include this zone into the clip, these cells will be used to analyze the neighbourhood characteristics of the cells located at the edge of the countries. The lower left x-coordinate, lower left y coordinate, the cell size and the number of rows and columns of all maps have to correspond exactly for all maps per country.

Switzerland is not a member of the EU and therefore no land cover information is present in the CORINE data set. Switzerland and Germany however, share borders. In order to measure neighbourhood effects, the accuracy improves if land cover information is available for Switzerland at least at the border region. Fortunately, a separate data set of land cover in Switzerland is available from the Swiss Federal Statistical office (SFSO) and Swiss Agency for the Environment, Forests and Landscape (SAEFL), but only for the year 1990. We have transformed the projection of this data set to the ETRS 1989 projection system used in the CORINE. Thereafter, we applied the same reclassification as before and finally, we merged the data set of Switzerland with the CORINE data set.
We also used the 1990 data of Switzerland to merge it with the CORINE data of 2000, because land cover information of 2000 is not available of Switzerland. Although, the data

does not exactly represent the land cover of 2000, the differences with the 1990 data will be small, but the performance of the analysis will improve compared to the situation where no data of Switzerland was available.

These steps are repeated for Spain and Germany for both 1990 and 2000 in order to complete the creation of the initial and final maps.

3.4.2.2 Region maps Neighbourhood Analyzer

We have used a shape file with the borders of all EU countries to create the region maps. We selected the country (Spain or Germany), changed the shape file into a raster file and we have reclassified all values in the corresponding country into the value one. The remaining cells are assigned the value zero. To make sure the region map involves exactly the same region and resolution, we used the characteristics of the initial map as output extent.

In order to check the results, we have made an overlay of the region maps and the land use maps. Apparently, at some locations the country boundaries do not match exactly with reality. In Germany, some lakes in the middle of Bavaria have been excluded, but they do belong to the German country. In Spain, some land parts (which belong to the see according to the EU border shape file) are in reality land and therefore have to be added in the research area. In other words, they have be assigned value ‘one’ in the region map.
No automatic solution is available to solve this problem, so we manually compared the land use maps and the region map and we changed the pixel value into one at that location when necessary.

3.4.2.3 Region maps Metronamica

The Metronamica model consists of multiple levels as explained before. At micro level, a CA-based model allocates the land uses at cell level. At macro level, a regional model defines the cell demands for each land use per year in each of the NUTS 2 regions for Spain and the NUTS 1 regions for Germany. For this regional model another two region maps have to be created. The work process corresponds with the creation of the region maps for the Neighbourhood Analyzer. Now, we use a shape file with the borders of all NUTS (Nomenclature des Unités Territoriales Statistiques) regions. We again converted this map to a raster format and reclassified the map so that every region has a unique value. The region outside the modelling area gets the value zero. The output extent has to be exactly the same as the previous maps. The same problem with the German and Spanish border occurred here. Fortunately, we only had to compare the region maps of the two countries with the NUTS region maps. The cells outside the boundaries were reclassified to the correct NUTS region.

3.4.2.4 Suitability and transportation maps

The suitability and transportation maps have both been adopted from the maps used in the LUMOCAP project. This project aims at delivering a tool for evaluating land use changes and the accompanied impact on the rural landscape. The suitability and transportation maps have been re-sampled to the correct resolution and have been clipped to the correct research extent. In contrast to the other input maps, the transportation map is a shape file originated from the GISCO database (GISCO, 2009). A reclassification has been applied to the following classes: highway, expressway, primary road and car ferry. The classification scheme can be found in appendix II.

3.4.2.5 Zoning maps
The zoning maps are based on the Natura 2000 zones. In every Natura 2000 area, an expansion of the land uses residential, industry and recreation is not allowed. The cells of these land uses already present are allowed to stay. For the other land uses, no restrictions have been applied.

3.4.3 Step 3: first calibration round

The following research objective will be dealt with in step three to six:

1. To determine the land use attraction and repulsion effects present between 1990 and 2000 in both Germany and Spain.
    a. Which attraction and repulsion effects exist and how do they develop over increasing distance?
    b. What are the differences of the attraction and repulsion effects in the two regions?

The third step of the research involves the first calibration round of the Metronamica model for both Spain and Germany. For each country, two calibrations have been made: the first calibration (1A) is based only on the settings of the neighbourhood rules (splines) and the second calibration (1B) is based on the neighbourhood rules, suitability, zoning, and accessibility parameters (see equation 2). We will use a standard calibration methodology based on trial and error. The purpose of the calibration is to tune the model in such way that the simulated map of 2000 based on the land use map of 1990 corresponds with the land use map of 2000 as good as possible. We will determine the 'quality' of the calibration with several statistics; cell by cell comparison methods (Kappa, Kappa* and Fuzzy kappa statistics) and cluster size based methods (clumpiness index and cluster size frequency analysis).

We do not seek for the highest values of these statistical measures, but our emphasis in this calibration is more on modelling the land use development patterns well. This because the Neighbourhood Analyzer does not measure cell location, but rather the relation between different land uses and the changes involved.

Furthermore, our simulated map will be compared with a simulated map created with a randomly created map. This random constraint match (RCM) first looks for changes in the land use maps of 1990 and 2000 and then randomly allocates the amount of changed cells in the 1990 map (Hagen-Zanker and Lajoie 2008). The result is a simulated map of the year 2000, but then with the changed cells randomly allocated. We want our calibrated model to perform better than the randomly allocated map.
We will now shortly describe the used statistics.

Kappa
The Kappa statistic will be used to compare the similarity of two maps at pixel level (Congalton 1991). Every pixel per land use class of the first map is compared with the second map. The result is a map with two values: equal or unequal pixel values. Values range from -1 to 1. A kappa value larger than 0 indicates there is more similarity than random, a Kappa value smaller than 0 indicates less similarity than random. A value of 1 indicated perfect discrimination of the two maps. In appendix III, the Kappa statistic calculation formulas are shown.

Kappa*
The calculation of kappa* is almost equal to the calculation of the standard kappa, but one important difference exists. The expected fraction of agreement P(E) is here corrected for land use persistence. The standard kappa value of two maps can be very high if only a small number of cells have changed, but the changed cells are all allocated wrongly. Kappa* corrects for the number of changed cells.
Kappa* takes a subset S of all cells of which cells with land use i are similar in the initial land use map, final land use map and the simulation result. In appendix III, you can find the formulas to calculate Kappa*.

Fuzzy Kappa
The fuzzy Kappa statistic is calculated in the same way as the standard Kappa statistic. The main difference is that in the calculation of this statistic the fuzziness of cell location and the fuzziness of the cell category are taken into account. For the fuzzy kappa calculations, we used a radius of 4 cells, an exponential decay function with a halving distance of 2 and a slope of 0.5. For an extensive description of this statistic, we refer to Hagen-Zanker et al. 2005.

Cluster size frequency analysis
For the comparison of urban regions of the two maps, we will use the cluster size frequency relationship. This relationship is created by plotting the log of the frequency against the log of the cluster size of an urban area. The graph shows the rate at which urban areas become less apparent as they become larger. This relation does not take the location of the urban areas into account, but is an accepted measure of the spatial structure of cities and regions. (White and Engelen 1993, White 2006)

Clumpiness index
For natural areas, we will use the Clumpiness index (CLUMP). This index measures the extent to which parcels of similar use are aggregated. The value of the clumpiness ranges from -1 to 1 (from maximally disaggregated to maximally aggregated) and equals 0 when the patch type is randomly distributed (McGarigal and Marks 1995, Lewis and Plantinga 2004).
In appendix III, the description of the formulas can be found.

Random Constraint Match (RCM)
Our simulated maps will be compared with a simulated map created with a Random Constrained Match (RCM). This RCM first looks for changes in the land use maps of 1990 and 2000 and then randomly allocates the changed cells of the 1990 map in the 2000 map. The result is a simulated map of the year 2000, but then with randomly allocated cells. One condition of our calibrated map is that it should result in better statistical results than the randomly allocated map (Hagen-Zanker and Lajoie 2008).

Calibration procedure
The first step of the calibration process involves the calibration of the neighbourhood rules. In the Metronamica model, this can be done by adapting the so called neighbourhood rules or splines (see figure 4). A neighbourhood rule describes the influence of a certain land use on another land use (or on itself). On the x-axis, the distance from the centre cell of a certain land use (in this case residential) is shown which is set to a radius of eight cells. The values on the y-axis are used to calculate the potential of change for a certain land use. As described earlier, a cell changes into the land use with the highest potential at that moment, but only when that type of land use still needs to be allocated. The height of the values at the y-axis is

only relative. In other words, the height of these values only indicates the difference in potential for a certain cell compared with all other neighbourhood rule values.

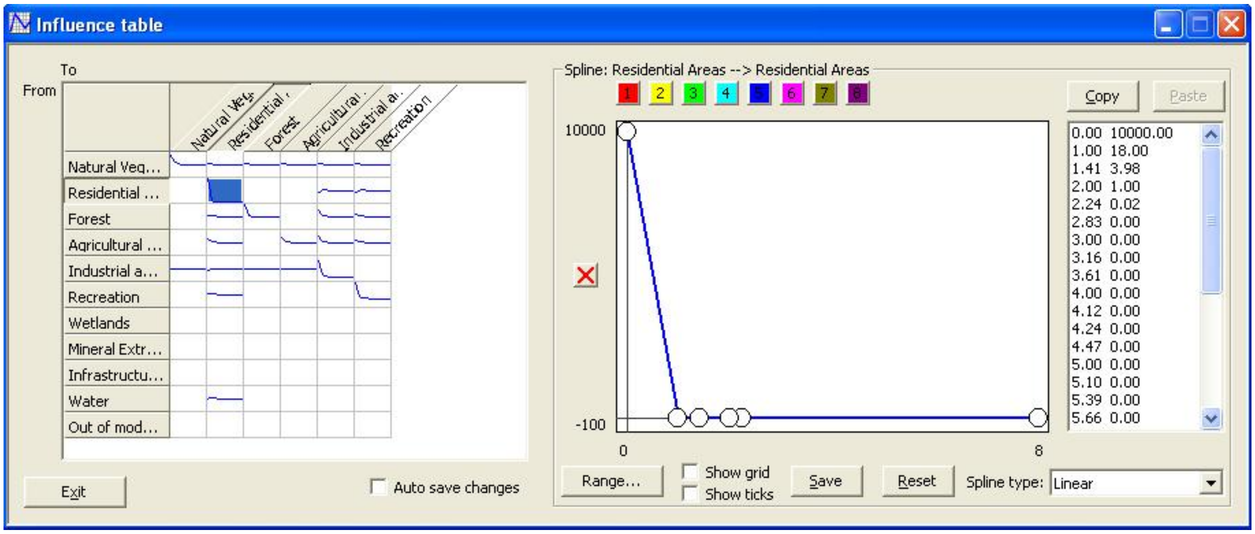


Figure 4: neighbourhood rules Metronamica model

Important land use properties can be modelled with three main neighbourhood rule properties: the inertia, tail and height of the neighbourhood rule

1. The inertia is the value at x=0 and represents the strength with which the current land use stays at the same location once allocated. In figure 4, the inertia of residential areas is 10.000 and compared to other land uses, this value is very high. Once residential areas are allocated, it is very hard to change this in the future.
2. The tail influences the size of the cluster that appears; the longer the tail, the larger the clusters eventually will be. Furthermore, a negative tail with a positive core limits the size of evolving clusters.
3. The height of the total function affects the size and shape of the cluster, the type of adjacencies between land uses and the location of the land use. A function with a higher height produces more regular cluster edges and can more easily replace other land uses (van Delden et al. 2007)

The calibration procedure goes as follows: the initial neighbourhood rules are set up based on expert knowledge. For example residential areas are almost always built next to already existing residential areas (figure 4) or industrial areas are mostly built at the edge of existing villages. Thereafter the model has to be run and the result has to be visually compared with the real land use map by means of a tool called Map Comparison Kit (MCK). In the MCK, several options exist to visually and statistically compare two raster land use maps. In appendix IV, tips and remarks of the Metronamica model and the MCK can be found.
Then, we decide what changes have to be made in the neighbourhood rules in order to obtain better results and we manually adapt these rules. This process is repeated until we believe the results are satisfactory. The quality of the calibration is based on a visual observation (are the land use patterns realistic and do they comply with the land use map) and the statistics. After the calibration of only the neighbourhood rules, the land use patterns of the simulated map should roughly correspond with the land use map.

The second calibration in this round (1B) involves the usage of suitability (S) and zoning maps (Z) and the manual adaptation of different accessibility parameters (A) as can be seen in

equation 2 in paragraph 3.3. The starting point of this calibration is the end point of the previous calibrations involving only the neighbourhood rules.
We created for every function and vacant land use class (residential, industrial and commerce, forest, agriculture, tourism and natural vegetation) suitability maps. These maps are extracted from the suitability maps used in the LUMOCAP project. The suitability is mainly based on the slope of the land and ranges from 0 (not suitable) to 1 (very suitable). The zoning maps are created also for the function and vacant land use classes and are based on the Natura 2000 policy. The Natura 2000 consists of different restrictive area types, but every type consists of a special protection area (SPA) and/or sites of community importance (SCI).

In this case we restricted the allocation of residential, industrial and commercial, and recreational areas in the Natura 2000 areas. All other function land use classes (forest and agriculture) and natural vegetation are allowed to expand in the Natura 2000 areas. The restricted land use types are not allowed, except for land use cells already present.
The suitability and zoning factors are taken into account for every cell with the calculation of the total potential per land use class.

The accessibility variable is mainly based on the distance to the road network. The calculation of the accessibility potential can be adapted by changing different model parameters that are enlisted below:

- Implicit accessibility: for every built-up land use (in this particular case: residential, and industrial and commercial areas) the implicit accessibility can be adjusted. The incorporated road network maps only consist of highways and primary roads. The smaller roads between towns and in urban areas are not present in these maps, but they are certainly increasing the accessibility of these areas. Fortunately, we can correct for this by the following factors for every built-up land use class:
    - Implicit accessibility of built-up area: this factor ranges from 0 to 1 and multiplies the accessibility of built-up area cells by the indicated value.
    - Implicit accessibility of non-built-up area: this factor also ranges from 0 to 1 and multiplies the accessibility of non-built-up area cells by the indicated value. The larger the difference of the values for built-up and non-built-up area, the larger the difference in accessibility of built-up and neighbouring non-built-up areas. High values of implicit accessibility for built-up areas and lower values for non-built-up areas result in a much higher accessibility for built-up compared to neighbouring non-built-up areas.
- Accessibility to links and nodes: for every road type (highway, expressway and primary road) and function or vacant land use, the following parameters can be adjusted:
    - Relative importance: the importance of the road type concerned compared to the importance of the other road types. This parameter can be seen as a sort of weight factor.
    - Distance decay: the strength of the accessibility over distance expressed in number of cells. The larger the distance effect, the larger the effect of a certain road has on a certain land use class.

Here, the same calibration method holds as before; by means of trial and error. The neighbourhood rules also need some small adaptations after incorporating the suitability, zoning and road network maps.

3.4.4. Step 4-6: analysis of neighbourhood relations

The second objective can also be investigated after performing step six.

2. To compare the neighbourhood effects of the land use map and a simulated map of both regions.
    a. What are the differences in the neighbourhood effects of the simulated map and the land use map and can they be explained?

The fourth step includes the analysis of the existing neighbourhood relations of the two CORINE maps of 1990 and 2000. These two maps are not the simulated maps, but obtained from satellite information. The Neighbourhood Analyzer will be used to measure the existing neighbourhood relations as described in chapter 3.2.
We also use the simulated maps of 2000, created in step three, and the real CORINE map of 1990 together as input of the Neighbourhood Analyzer.

We will use the output of these three runs of the Neighbourhood Analyzer to create attraction and repulsion graphs of the different land use interactions in step five. These graphs show the attraction and repulsion effects of different land uses at one single land use for different neighbourhood distances. With these graphs, we can compare the different land use interactions and their development over distance in step six.

In step six, the neighbourhood relations will be investigated by means of influence graphs (for the CORINE 1990-2000 map and the two CORINE 1990 - simulated 2000 maps). Not only can we compare the different interactions over time, we can also compare the differences in neighbourhood relations of the calibrated map and the real map of both countries. Furthermore, a comparison of these relations between Spain and Germany is possible.

We will only measure the influences of the vacant and function land use classes on residential and industrial areas. These two land use classes have increased in size significantly during the 10 years of our research period and the expansion of these classes is all based on human decision making. Therefore, it is of interest to investigate the neighbourhood of these two land use classes.

3.4.5 Step 7-9: second calibration round, sensitivity analyses and statistical comparison

The third research objective can be answered after completing step seven to nine.

3. To find out whether we can improve the calibration process with the neighbourhood relations found in the real maps.
    a. Can the calibration be improved in both countries with the gained neighbourhood effect knowledge?
    b. Can the results of this research be used in the automation of the calibration procedure?

Unfortunately, we can not use the outcomes of the Neighbourhood Analyzer directly for the calibration of the model, because the neighbourhood effects we have found are measured over a 10 year time period. These effects are however non-linear over time and therefore not scalable to a 1 year value. Therefore, we use a more qualitative approach to improve the manual calibration with the knowledge gained from the land use changes really occurred during this time period

In step seven, the differences found in the influence tables (step six) will be implemented in a new calibration trial. With the knowledge gained from the neighbourhood interactions from the run with the two CORINE datasets, the influence tables in the Metronamica model will be manually adapted. Only the influences on the residential and industrial land use class are adapted.
The outcome of this calibration will be compared with the outcome of the first calibration by means of several statistics described in paragraph 3.4.3.

In step eight, a sensitivity analysis will be performed in order to test the sensitivity of the neighbourhood rules. How sensitive are these rules if small changes in the attraction and repulsion effects are made? We will use the effects of residential areas on other residential areas as a test case. For this interaction, we will use the attraction and repulsion settings of calibration 2 as a starting point. We will run the model several times with varying settings of this interaction. The following percentages of the original second calibration settings are used in the analyses: 10, 50, 80, 90, 110, 120, 150 and 190%. The results are thereafter compared with attraction and repulsion graphs and the same statistics as used in step seven to measure the sensitivity.

Finally, in step nine, conclusions will be drawn with the results found and recommendations will be made on how to use these findings in a (semi-automatic) calibration procedure.

4. Results

In this chapter, we will describe the results following our research objectives. The chapter is set up as follows: in chapter 4.1 the results are shown for the first research objective. We will describe the land use interactions that were present between 1990 and 2000 in Spain and Germany. In chapter 4.2, the second research objective is dealt with. The land use interactions found from the land use maps are compared with the interactions found at the first calibration session. Also the interactions found in the two different countries are compared. Finally, in chapter 4.3 an extensive description of the results of the first calibration is given. This result is thereafter compared with the results of the second calibration. The question is whether this has resulted in an improvement or not and this is also the third and final research objective.

4.1 Land use interactions 1990-2000 – research objective 1

In this paragraph, the following research questions will be answered:

1. To determine the land use attraction and repulsion effects present between 1990 and 2000 in both Germany and Spain.
    a. Which attraction and repulsion effects exist and how do they develop over increasing distance?
    b. What are the differences of the attraction and repulsion effects in the two regions?

4.1.1 Results – objective 1

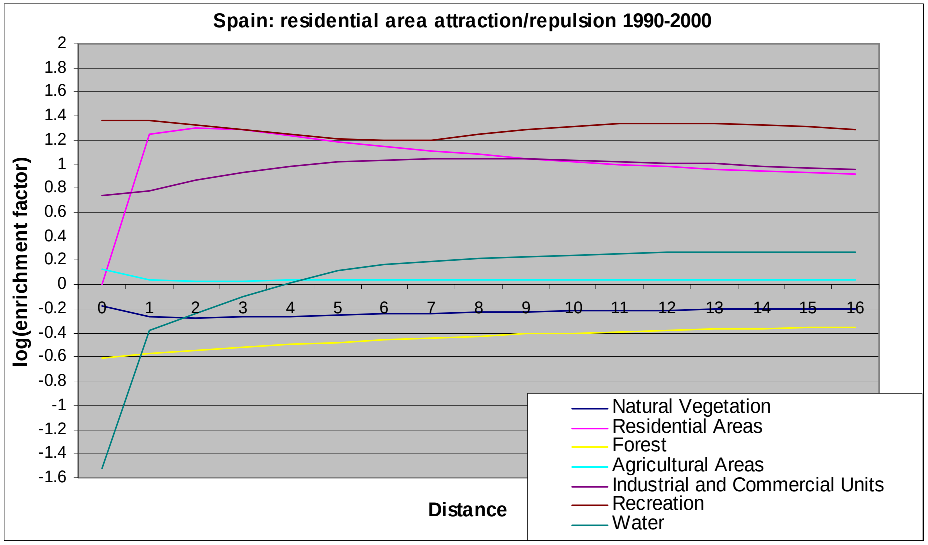
In figure 5 for all vacant and function land use classes and for the feature land use class water, the attraction and repulsion effects on residential and industrial areas are shown for both countries. The influence on the other land use classes are not shown here, but can be found back in appendix V and VI. The attraction and repulsion are calculated as the logarithmic function of the enrichment factors as explained in the methodology section.

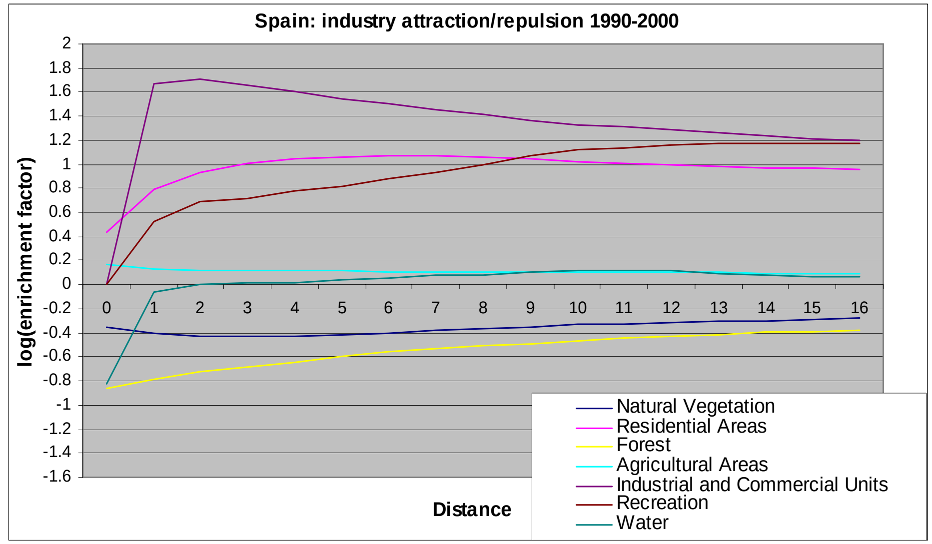
A first impression of the four graphs shown below is that the rough patterns seem similar, both for the two countries and for the two land uses. New residential and industrial areas in both Spain and Germany are repulsed by natural vegetation and forest and are attracted by already existing industrial, residential and recreational areas. Agricultural areas and water have almost no influence on industrial and residential areas. At x = 0, the agricultural fields have a slightly positive value at all graphs which indicates that these fields are converted into residential and industrial areas.

If we look at the scale of the y-axis, we can see that the effects in Spain are somewhat stronger compared to those in Germany.

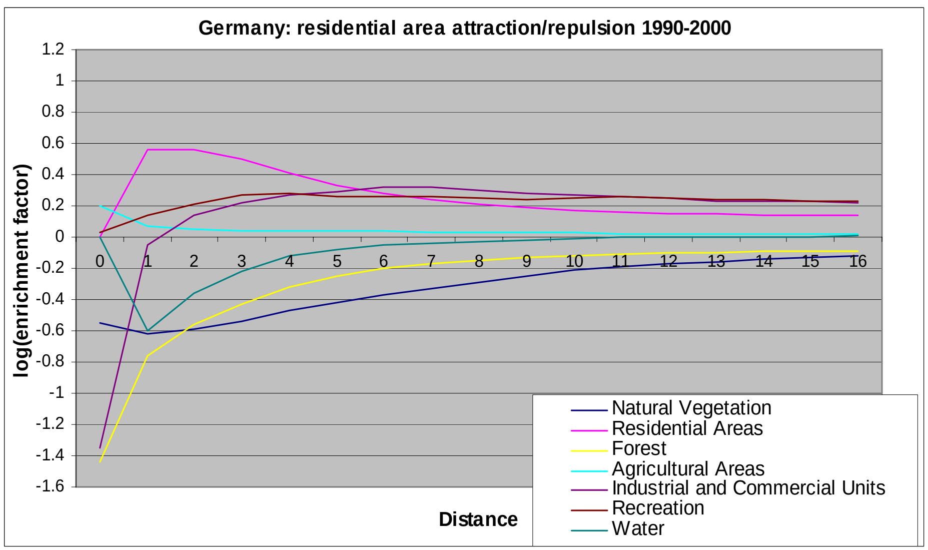
The effect for most land uses decreases when distance increases. In other words, the attraction or repulsion effect is weaker at large distance. Another interesting pattern appears at large distances, especially for the land use in Spain. Here, the attraction and repulsion effects are still quite large at a distance of 16 cells (=4km), whereas in Germany these effects are much smaller.

Spain





Germany



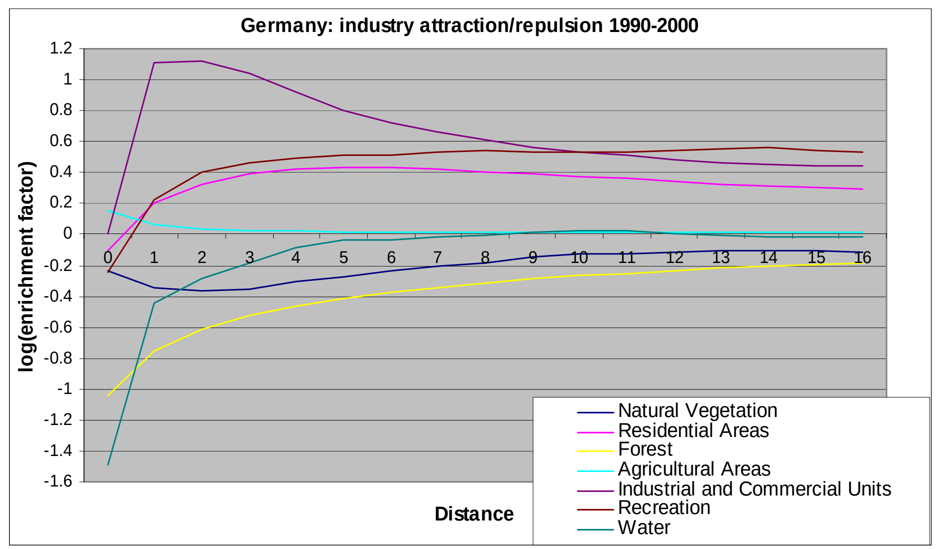


Figure 5: attraction and repulsion graphs for the land use maps. Top left: residential areas Spain, top right: industrial areas Spain, bottom left: residential areas Germany and bottom right: industrial areas Germany.

4.1.2 Discussion – objective 1

The results in Spain and Germany seem logical and are in accordance with our expectations. Industrial and recreational areas attract new residential areas, but industrial areas attract them strongest at approximately 1.5 km distance. Industrial areas strongly attract other industrial areas and in less sense residential and recreational areas attract industrial areas. In this case, residential areas do not actively attract industrial areas, but the fact that these two land uses are already located at close distances from each other results in a positive value in the graph above. Moreover, the differences between residential areas and industrial and commercial areas are not always easy to see at satellite images. Classification errors can be made for these land use categories in the CORINE maps.
Agricultural areas are present just outside built-up areas. The amount of agriculture in the neighbourhood of residential and industrial cells has not changed much. However, some agriculture has been transformed into residential or industrial areas which can be seen at the slightly positive values at x=0. Even further away from the built-up area, forested and natural vegetated areas can be found. In the graphs, residential and industrial areas are repulsed by natural vegetation and forest, because the amount of these land uses in the direct neighbourhood of residents and industry has decreased during 1990 to 2000.

The difference in magnitude of the attraction and repulsion effects can be caused by the fact that in Spain the industrial and residential areas have, relative to the country's size, expanded more during these 10 years compared to Germany. The probability of a built-up cell to be present in the neighbourhood of another built-up cell has increased which also is an explanation of the effects still present at larger distances (up to 4 km).

Verburg et al. (2004) have also created attraction and repulsion graphs, but within a different setting. They have modelled the Netherlands at a 500 m spatial resolution and they have measured changes between 1989 and 1996 also for the land uses industry and residential area. The main similarity with our graphs is the order of the land uses. Here, also industrial, residential and recreational areas do attract new industrial and residential sites. Agricultural land has almost no influence and forest and nature repulse industry and residential areas which complies with our findings as well. However, main differences are also present. The strength of the effects is much smaller at Verburgs research which can be assigned to the geographically different research area and the amount of land use change during the research period.
Furthermore, the strength of the effects at larger distances (up to 4 km) is much stronger in our graphs. The values at Verburg do not exceed 0.3 at this distance whereas in our case, values easily exceed 0.4 for Germany and even over 1 for Spain. Also, the shapes of certain land use interactions differ which perhaps has to do with the different scale, geographical region and the amount of land use change.

4.2 Simulation vs. land use map neighbourhood effects – research objective 2

In the following paragraph, we will discuss the results of the following research objective:

2. To compare the neighbourhood effects of the land use map and a simulated map of both regions.
    a. What are the differences in the neighbourhood effects of the simulated map and the land use map and can they be explained?

In chapter 3, we explained the calibration procedure. In the first calibration round, we calibrated twice. The first calibration (1A) is only based on neighbourhood rules and the second calibration in the first round (1B) is based on neighbourhood rules, accessibility, zoning, and suitability. The result map of the calibrations has been compared with the original land use map of 2000 for both regions. Attraction and repulsion graphs have been created for both maps. In figure 6a, we show the difference of both graphs for calibration 1A and the land use map. In figure 6b, we show the difference of both graphs for calibration 1B and the land use map. The more the separate lines, that represent the attraction of different land uses, are closer to the x-as (difference of attraction = 0), the better the neighbourhood configuration resembles the land use map neighbourhood configuration. With neighbourhood configuration, we mean the locations and type of land use in the neighbourhood of a cell.

4.2.1 Results – objective 2

For both countries and both calibrations, the differences in neighbourhood configurations are larger at smaller distance. At larger distances however, the neighbourhood patterns of the simulation resemble the existing patterns of the land use map. The differences are largest at x = 0 for most land uses. In the case of Spain, most land uses attract industry and residential areas too little which can be seen at the negative values in the difference graphs. Furthermore, in the simulated maps, compared to real data, natural vegetation repulses industry and residential area too much in both countries according to the large positive values of this neighbourhood effect in figure 6b. Another interesting point is the small peak in the neighbourhood function of residential areas in the graphs of residential areas at x=0. These peaks indicate that residential cells attract other residential cells too much in their direct surroundings.

The differences of the two calibrations mutually are actually small. Except for industry in Spain, the shapes and even the values of the graphs correspond much.

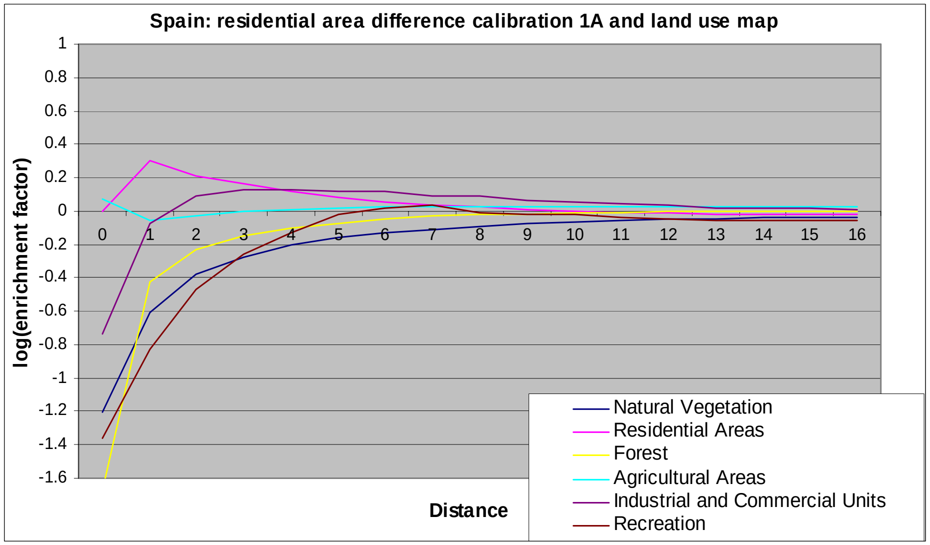
4.2.2 Discussion – objective 2

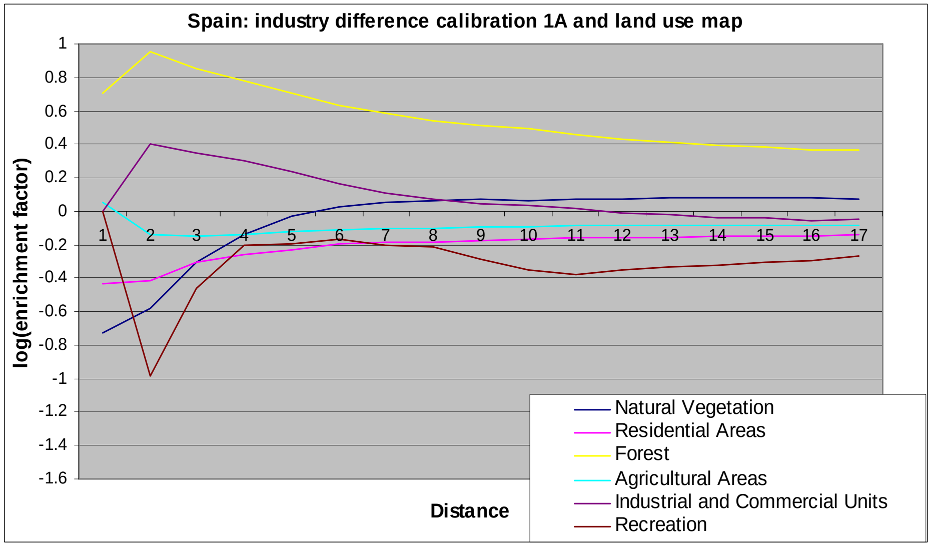
The main target of the first calibration round is to simulate the land use development patterns as well as possible. Especially at distances larger than 4 cells (1 km), the patterns do resemble the real land use patterns. The calibrated neighbourhood rules (splines) are never set further than 4 cells, so apparently these settings did indeed not influence land use pattern at larger distances. At shorter distances however, the differences are larger.

The large differences at x=0 in the results can be explained by the fact that the inertia effect of most land uses is too high in the model. In other words, if the land use has been allocated, the chance that it will be replaced by another land use is very small. These values are easily adapted in the second calibration run.

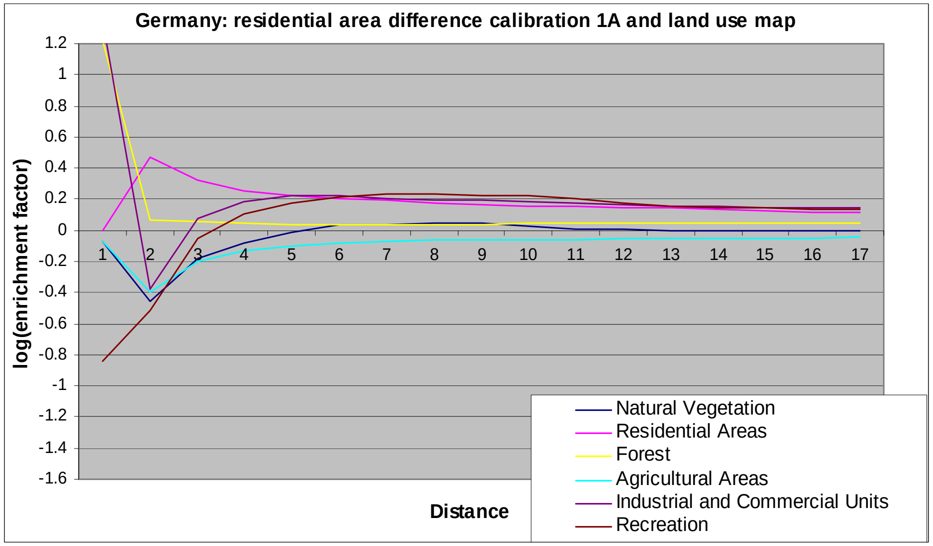
The differences of the neighbourhood configurations for the two calibrations are very small. However, the land use clusters in calibration 1A (only neighbourhood rules) are very large and blobby and do not correspond with the real land use clusters (visual assessment of simulated maps, see also paragraph 4.3). Indeed, the land use configuration of his calibration do correspond with calibration 1B, the land use patterns are not realistic.

Spain





Germany



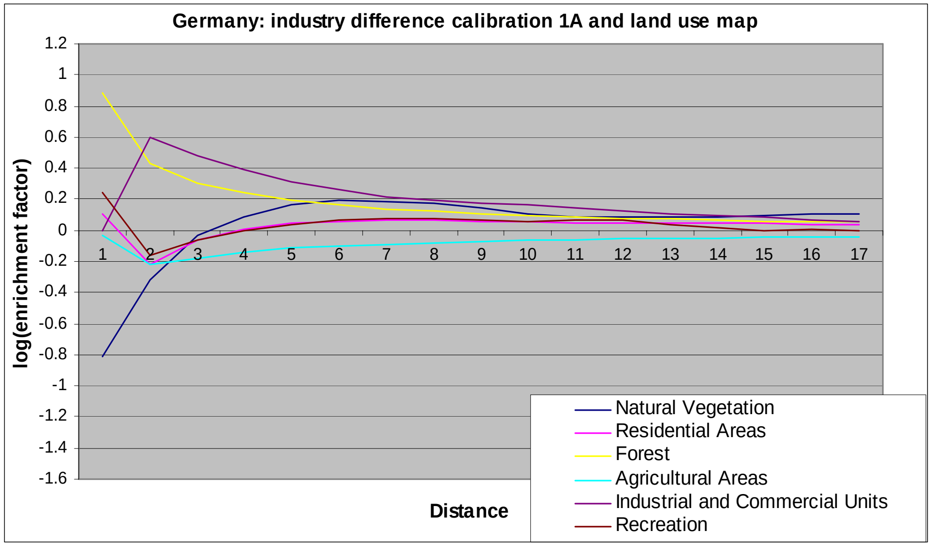
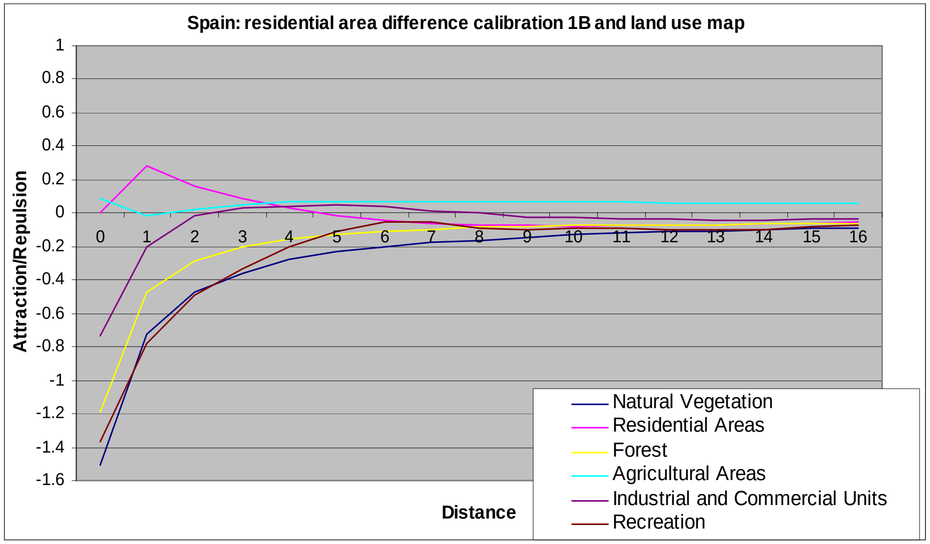
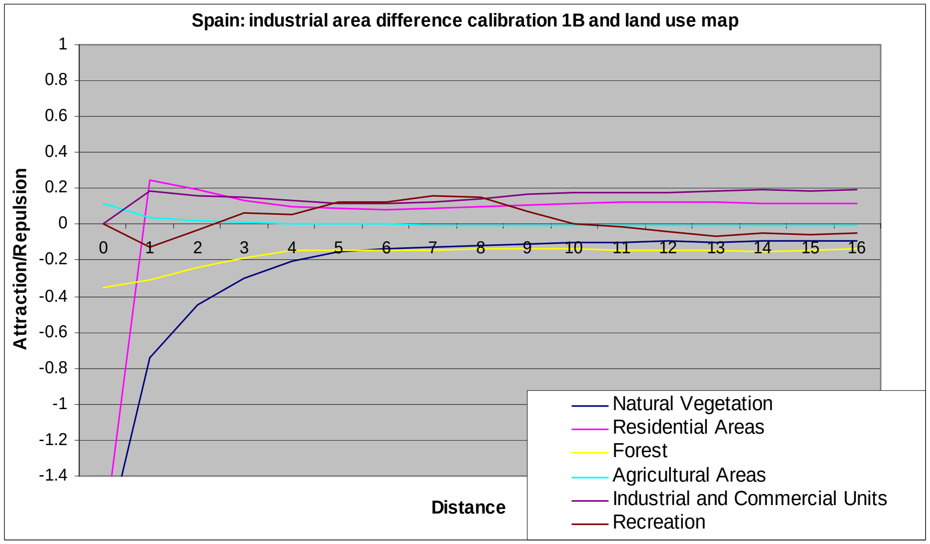


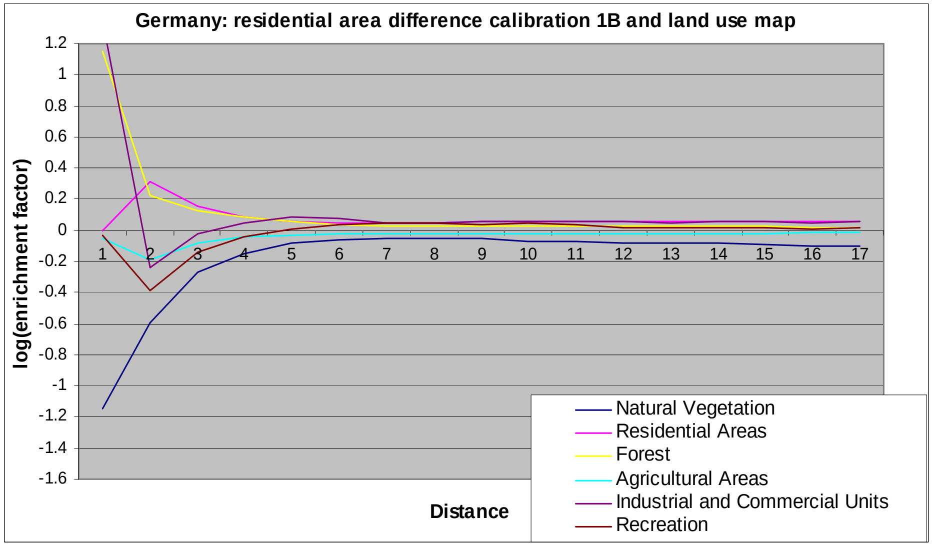
Figure 6A: attraction and repulsion graphs difference calibration 1A and the land use maps. Top left: residential areas Spain, top right: industrial areas Spain, bottom left: residential areas Germany and bottom right: industrial areas Germany.

Spain





Germany



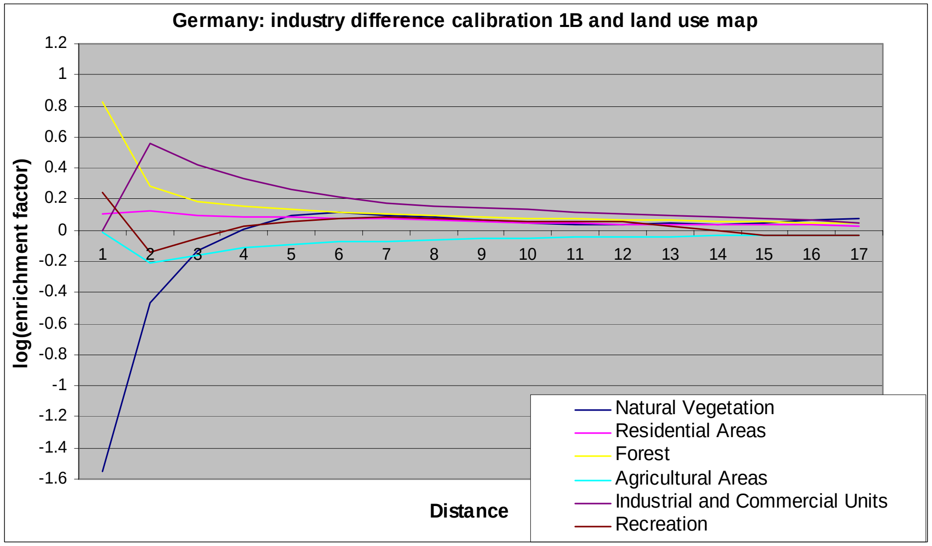


Figure 6B: attraction and repulsion graphs difference calibration 1B and the land use maps. Top left: residential areas Spain, top right: industrial areas Spain, bottom left: residential areas Germany and bottom right: industrial areas Germany.

4.3 First vs. second calibration – research objective 3

In this paragraph, the following research objective is worked out:

3. To find out whether we can improve the calibration process with the neighbourhood relations found in the real maps.
    a. Can the calibration be improved in both countries with the gained neighbourhood effect knowledge?
    b. Can the results of this research be used in the automation of the calibration procedure?

We have calibrated the model for Spain and Germany for the second time in order to improve the neighbourhood patterns of the first calibration round. Our aim was too decrease the difference in enrichment factor of the first and second calibration as much as possible. We want to decrease all differences between 0.2 < y< -0.2 as much as possible. We will compare the second calibration with the calibration only based on neighbourhood rules (1A) and the calibration based on neighbourhood rules, accessibility, suitability, and zoning (1B). The second calibration is based on the same factors as calibration 1B, because it results in more realistic land use clusters compared to calibration 1A.

This chapter consists of two parts. In the first part, we will describe the attraction and repulsion graphs of the second calibration for both Spain and Germany. In the second part, we will further discuss the results for each country separately.

Also, some cut-outs are shown with parts of Spain for showing different types of development patterns in these countries. Finally, we have run the model until the year 2030 in order to check the models exploration performance. The model has not been calibrated for this purpose, but we wanted to check for future behaviour with the current neighbourhood rules.

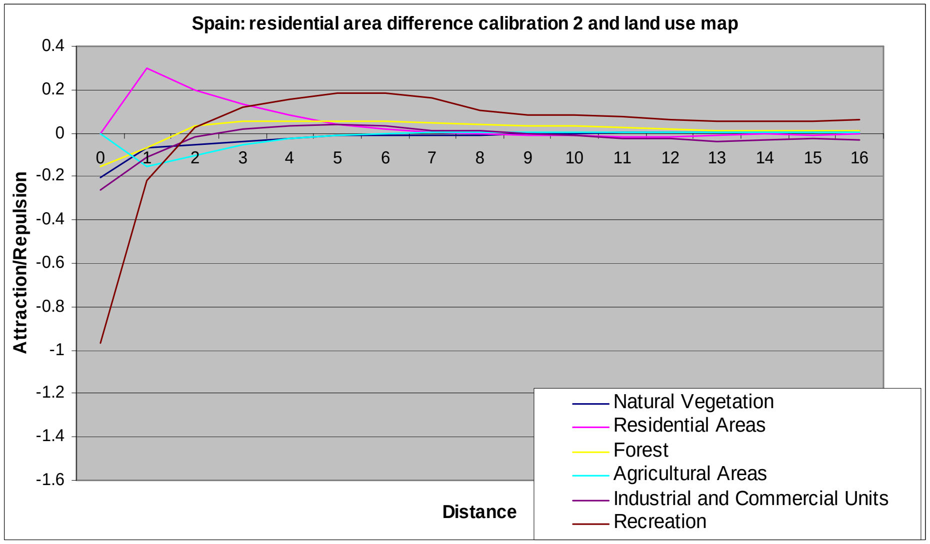
4.3.1 Attraction and repulsion graphs Spain and Germany second calibration

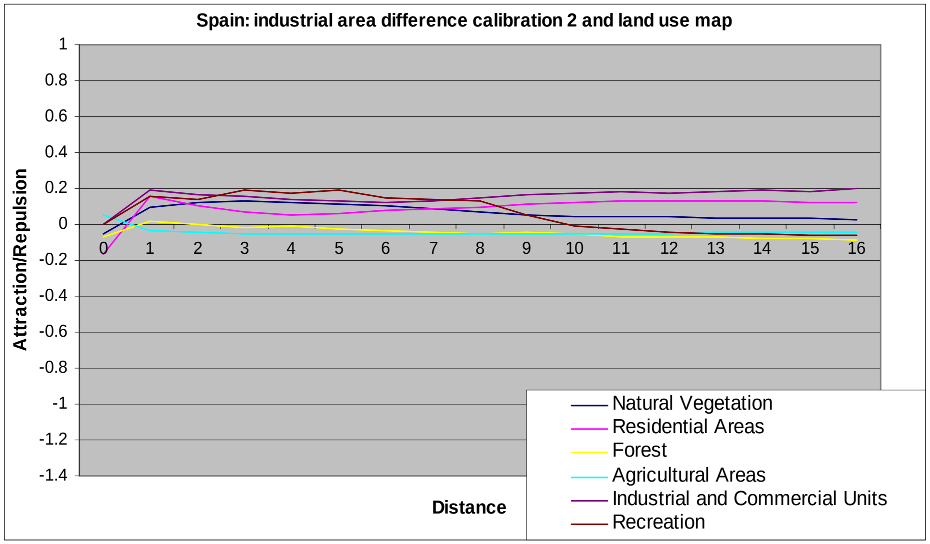
In figure 7 the four attraction -and repulsion graphs are shown for the second calibration. These graphs are the result of the improved second calibration which is modelled in order to minimize the difference in attraction and repulsion for the simulation and the land use map of both countries. If we compare the graphs below with the graphs of the first calibration (figure 6A and 6B), we can immediately see that the lines in the graphs below are much closer to the x-axis which indicates a decrease of the differences between the simulation and the land use map. In other words, during the second calibration, we significantly improved the neighbourhood compositions of the simulated map. Most lines lie between 0.2 < y< -0.2, but some exceptions exist.

First of all, the influence of recreational areas on residential areas deviates much from the x-axis. Not much cells are classified as recreation compared to the total number of cells. Also, the recreational land use class is very diverse and exists of urban green areas, but also of theme parks such as Movieworld Germany. Because of these reasons, it is very difficult to model the recreational land use class.

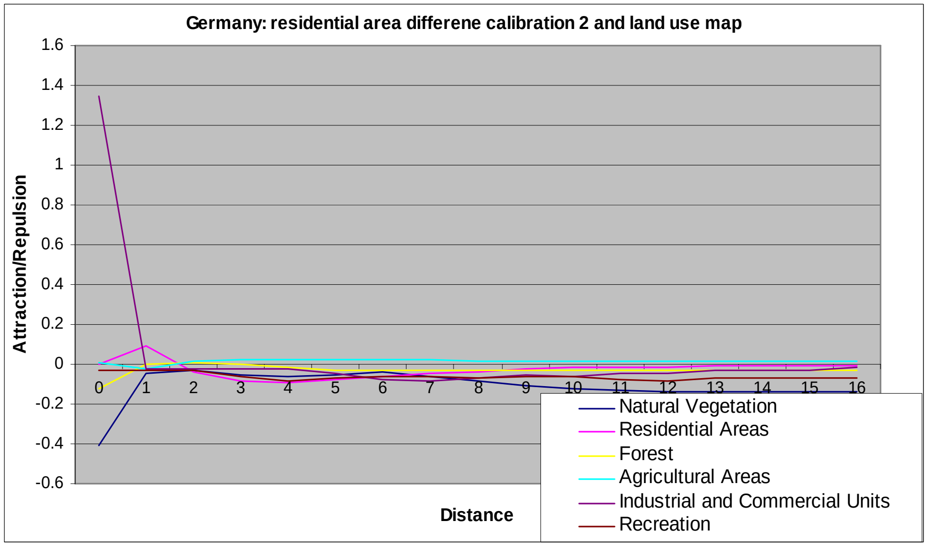
Second, too little industrial cells are converted into residential cells according to the high value at x=0 in the bottom left graph. Between 1990 and 2000, only five residential cells have changed into industrial cells. In our calibration, no cells have transformed like this, due to the high inertia of residential cells. The graph has such a low value due to the relative large difference of converted cells (0 vs. 5 cells). The inertia can however not be changed because otherwise far too much residential areas will be replaced by industrial areas and the graph will swap to values much below the x-axis. In short: the best option has already been adopted in this case. Finally, too much residential cells are directly allocated next to other residential cells in Spain, caused by the fact that some new villages have appeared, but we were not able to model these correctly due to model restrictions.

Spain





Germany



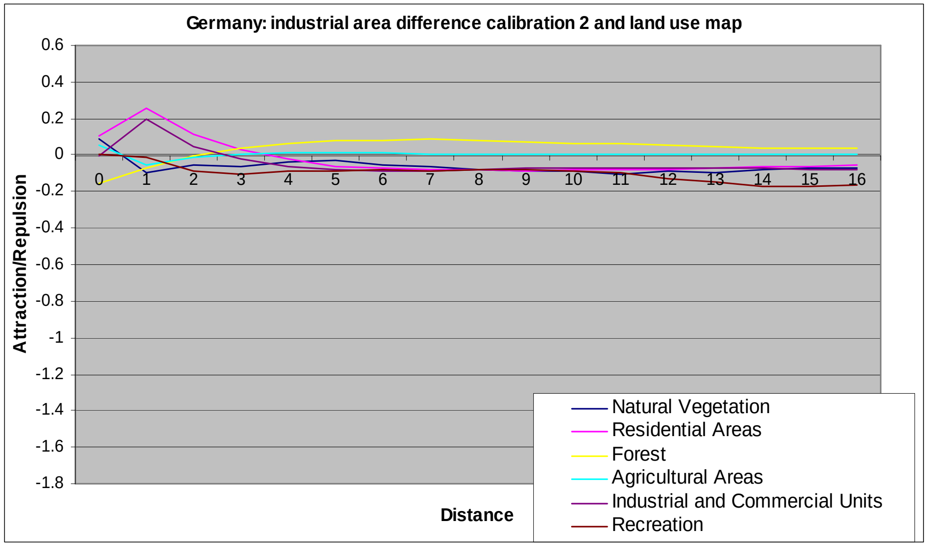


Figure 7: attraction and repulsion graphs difference calibration 2 and the land use maps. Top left: residential areas Spain, top right: industrial areas Spain, bottom left: residential areas Germany and bottom right: industrial areas Germany.

4.3.2 Results Spain– objective 3

In this paragraph, we will describe the results of the second calibration of Spain and compare these with the results of the first calibration.

In table 4, the results of the Kappa statistics are shown. The table shows results for the five Random Constraint Match maps (RCM 1-RCM 5), the calibration only with neighbourhood rules (calibration 1A), the calibration with the neighbourhood rules, zoning, suitability and accessibility activated (calibration 1B) and the second calibration (calibration 2). Kappa statistic values are given for the total map and for the residential and industrial land uses separately.

As can be seen in table 4, calibration 1A already has a higher fuzzy Kappa, but equal Kappa compared to the RCM maps. Calibration 1B and 2 perform even better and have a Kappa value of 0.945. However, the differences for the fuzzy kappa values are much larger. The RCM maps have a fuzzy kappa value of 0.896, calibration 1A has a value of 0.907 and calibration 1B and 2 have a fuzzy kappa of 0.911. Also for Kappa*, all calibrations perform better than the random map with the highest Kappa * value for calibration 1B and 2.

Table 4: results Kappa statistics Spain for the random maps and the three calibrations. Bold numbers indicate the best value for this statistic.

	Random maps	Calibration 1A	Calibration 1B	Calibration 2
Residential area				
Kappa	0.861	**0.878**	0.871	0.872
Fuzzy Kappa	0.876	**0.924**	0.921	0.920
Industrial area				
Kappa	0.623	**0.653**	0.651	0.647
Fuzzy Kappa	0.662	0.737	**0.741**	0.737
Total map				
Kappa	0.943	0.943	**0.945**	**0.945**
Fuzzy Kappa	0.869	0.907	**0.911**	**0.911**
Kappa*	0.000	0.019	**0.073**	**0.073**

For the land uses residential and industrial separately, the Kappa statistics show an opposite result. Here, the calibration which only involves neighbourhood rules has by far the highest values of Kappa, except for the fuzzy Kappa of industrial areas which is highest for calibration 1B.

In table 5, you can find the results for the clumpiness index. The clumpiness index is mostly used for natural land use types and serves as a measure for aggregation. This index ranges between -1 and 1 (from maximally disaggregated to maximally aggregated) and equals 0 when the patch type is randomly distributed. The better the clumpiness index values resemble the values for the land use map, the better the result is.

The clumpiness values of the RCM maps for all land uses are smaller than the values for the land use map. Calibration 1A has on the other end only higher clumpiness values. The values for Calibration 1B and 2 are only slightly higher compared to the land use map and gain the best result. In calibration 2, the value for industry has improved significantly, but the value for residential has not changed.

Table 5: calibration results Clumpiness index Spain. Bold numbers indicate best resemblance with land use map

	Natural vegetation	Agriculture	Forest	Residential	Industry	Recreation
Spain 2000	**0.718**	**0.773**	**0.718**	**0.661**	**0.608**	**0.617**
RCM 1	0.691	0.761	0.690	0.564	0.377	0.311
RCM 2	0.691	0.761	0.691	0.564	0.377	0.310
RCM 3	0.691	0.761	0.691	0.564	0.376	0.311
RCM 4	0.690	0.761	0.691	0.564	0.376	0.311
RCM 5	0.691	0.761	0.691	0.564	0.377	0.311
Calibration 1A	0.732	0.785	0.741	0.704	0.651	0.771
Calibration 1B	**0.727**	**0.782**	**0.723**	**0.688**	0.623	**0.533**
Calibration 2	**0.727**	**0.782**	**0.723**	**0.688**	**0.603**	0.520

The cluster size frequency analysis shows the rate at which clusters become more numerous as they become smaller (White 2006). In this case, we investigate residential clusters only. A log-log graph has been plotted with on the x-axis the logarithm of the cluster size (in cells) and on the y-axis the logarithm of the cluster frequency.
In figure 8, the cluster size frequency graphs are shown for the land use map, the three simulations, RCM map and a 2030 simulation based on calibration 1B settings. The shape of all graphs is more or less the same, but some differences can also be seen.

The larger residential clusters in simulation 1B are on average more numerous than the land use map clusters which can be seen by the higher value at x=0 and by the similar slopes (the line runs parallel, but lies a bit higher). The lines from calibration 1A and calibration 2 are almost similar. Compared to the residential clusters in the land use map, more small and medium sized cluster are present in the maps of the calibrations.
The randomly allocated map has a very large number of residential areas of only one cell (not visible in the graph below) which is of course due to the randomly allocated residential cells that form single cell clusters. The clumpiness index values of the RCMs are indeed lower than the land use map values.
The map of the simulation for the year 2030 contains a great number of larger clusters.

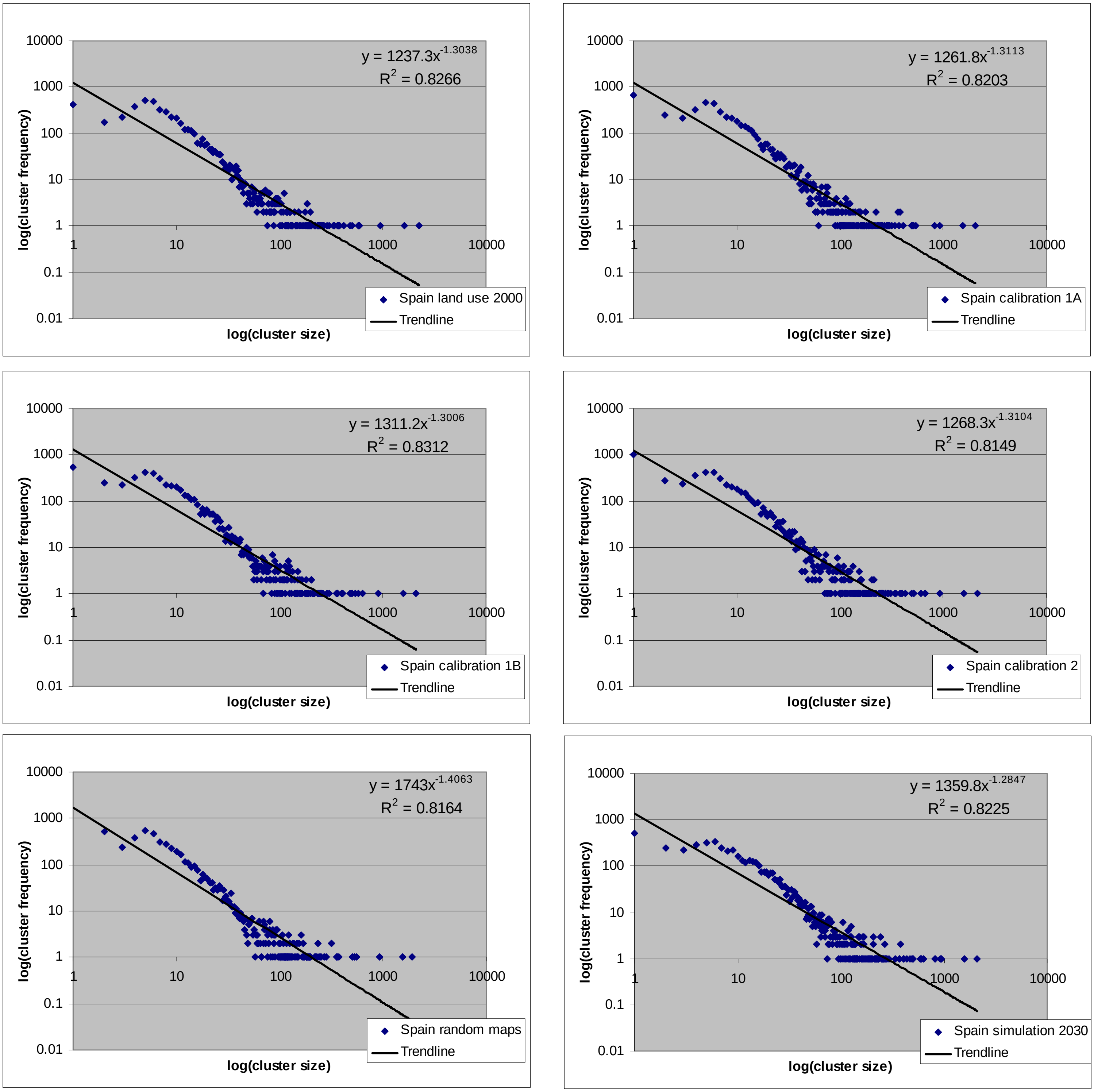


Figure 8: Cluster size frequency analyses results for Spain. Graphs represent the analysis of the land use map (top left), the simulation with only the neighbourhood rules (top right), the total first simulation (middle left), the second calibration (middle right), the RCM map (below left) and the simulation of 2030 (below right).

4.3.3 Discussion Spain – objective 3

In this chapter, the calibration results of Spain will be discussed.

Kappa values

The kappa values of the simulated maps are not much higher than the values of the RCM maps. The main reason for this is the size of the country and the number of cells involved. The number of changed cells in the simulation period compared to the total number of cells in Spain is very low (only 1.3 %). Therefore, to increase the kappa statistic, quite a number of cells have to be allocated at exactly the right location. Policy decisions are not taken into account in this model, so to allocate a cell exactly at the right location only based on zoning, suitability, neighbourhood rules and accessibility is very difficult. A large part of the increase in kappa from calibration 1A to calibration 1B can be ascribed to the introduction of network deltas. This function puts feature land use classes such as mining areas and airports at the right location during the simulation, because they are not actively modelled. This function has not been used in calibration 1A.

The Kappa* values are all higher than zero which indicates that the results are better than expected by chance. Also here, these values are highest for calibration 1B and 2.

The fuzzy kappa statistic in contrary, takes fuzziness of location and classification into account. The fuzzy kappa values for the simulated maps are much higher than the RCM maps. A cell neighbourhood with a radius of four cells is used for the calculation of the fuzzy kappa and the value is corrected for autocorrelation. In other words, the cells in the simulated maps are much better allocated than the RCM maps if we take the fuzziness of location and classification of a neighbourhood with a radius of four cells into account.

The highest kappa values for the separate land use classes residential and industrial areas are found at calibration 1A. In this calibration, the expansion of residential areas is only based on the neighbourhood of the cells which results in large and round clusters. In reality, smaller and more complex shapes are formed, but close to already existing residential areas. The large clusters in the calibration are also formed next to already existing residential areas and therefore much of the residential cells are exactly at the right location which results in high kappa values.

Clumpiness index

The clumpiness index values for all RCM maps are lower than the values for all land uses in the land use map. Due to the randomly allocated cells, the aggregation is weak which explains the lower values for the clumpiness index. The results of calibration 1A have however only higher values for this index than the land use map. This is caused by the fact that cells are often allocated next to already existing cells of that land use type which results in larger clusters. The best results are found for calibration 1B and 2. The aim of the second calibration is to improve the first one based on the neighbourhood relations found earlier. We have only tried to improve the neighbourhood configurations of residential and industrial land use classes. The clumpiness index of residential areas has not been changed during the second calibration, but the neighbourhood configurations have certainly improved (figure 6A, 6B and 7). One recognized problem of the enrichment factor is the fact that multiple neighbourhood compositions can result in the same value for the enrichment factor. In other words, the exact location of a land use cell in the neighbourhood of another cell does not matter as long as that cell is at the same distance from the land use cell. The neighbourhood composition can be improved, but the clusters that are formed do not have to change as well.

The clumpiness index value for industrial areas however has significantly improved after the second calibration.

Cluster size frequency analysis
The residential clusters in calibration 1A consist of simple geometric shapes, because their growth is only dependant on their neighbourhood. New residential pixels are allocated next to already existing clusters, both small and large. The slope of the graph of calibration 1A is therefore a bit steeper compared to the land use map.
The residential clusters in calibration 1B, when accessibility, zoning and suitability also are activated, have more realistic but complex shapes. A larger number of clusters between 100 and 1000 cells are present here, because mainly the larger towns grow in this simulation. This also explains the very small slope difference of the trend lines.
In the RCM maps a large number of one cell size clusters are present (due to the random allocation of residential pixels) and that is why this graph is much steeper than the graph of the original land use map. The simulation for the year 2030 contains many clusters with a size ranging from 100 to 1000 cells. With the present settings, middle size cities will grow strongly. However, the shapes of these cities and industrial regions are not realistic. In figure 9, the simulations for Madrid and Valencia are shown for the year 2030. Especially the shape of Valencia looks very clumpy. These calibration settings seem not very suitable for predicting the development of Spain 30 years ahead. In this research, we do not want to explore future land use changes, but this future simulation is only given to show how it looks with the present settings.

Calibration process Spain
The main problem we encountered during the calibration of Spain is the modelling of large regional differences. As Verburg 2004 also encountered, the calibration results improve if different regions are calibrated separately. Different cities have different growth patterns. The urban growth in a city such as Madrid is mainly concentrated next to already existing built-up area, but in cities such as Valencia and Barcelona the growth is much more sprawled. In figure 9 you can see the differences in growth pattern for the cities Madrid and Valencia. In Madrid, the growth is concentrated around the already existed city, but in Valencia, the growth is more sprawled and concentrated along the roads entering and leaving the city.
Another example of interregional differences is the growth of nature areas. In some areas, more forest is planted in the modelled period, but in other regions, forests have been cut in order to keep the landscape open. These differences in developments cannot be modelled both, because they are exactly the opposite. Therefore, the main difficulty in the calibration procedure is finding those settings that cover multiple land use development patterns.

Another difficulty is the modelling of very small patches of residential, industrial and recreational areas that exist at larger distances from roads. Some of these areas expand in reality during the modelling period, but the potential in the model for these land uses are very small due to weak neighbourhood effects and accessibility. This explains the fact that the cluster size frequency distribution of the calibrated map 1B contains more, somewhat larger, clusters compared to the original land use map. The simulation that involves only the neighbourhood rules in the calculation of the potential does not take accessibility into account and therefore these outlying towns have a larger growth potential.

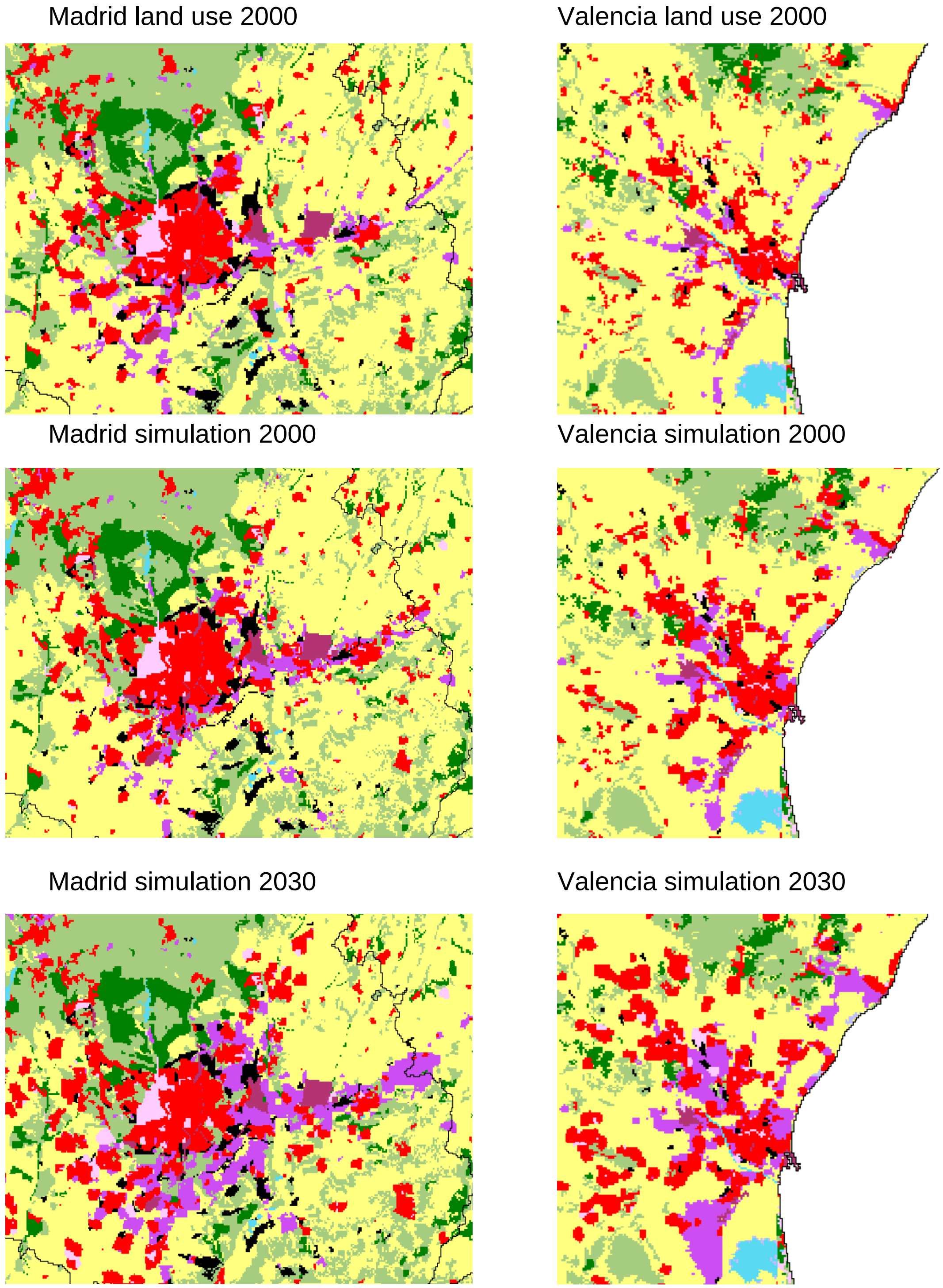


Figure 9: cut-outs simulations Spain. On the left site from top to bottom: Madrid land use map 2000, Madrid simulation 2000, and Madrid simulation 2030. On the right side from up to down: Valencia land use map 2000, Valencia simulation 2000, and Valencia simulation 2030.

4.3.4 Results Germany – objective 3

In table 6 the kappa and fuzzy kappa values are given for the different Random Constraint Match (RCM) maps and for the different calibrations in the same way as for Spain. Here again, calibration 1A only based on neighbourhood rules, has most industrial and residential cells placed at exactly the right location (Kappa: 0.955 and 0.827 and fuzzy Kappa: 0.963 and 0.887). Calibration 1B has the best overall performance for both the Kappa and fuzzy Kappa statistic (0.969 and 0.956 resp.). The second calibration has lower values for both statistics. All calibrations perform better than the random maps. Also for Kappa*, calibration 1B performs best, even better than calibration 2. The Kappa statistic outcomes resemble those of Spain; calibration 1B has the highest overall Kappa values.

Table 6: results Kappa statistics Germany for the random maps and the three calibrations. Bold numbers indicate the best value for this statistic.

	Random maps	Calibration 1A	Calibration 1B	Calibration 2
Residential area				
Kappa	0.953	**0.956**	0.955	0.954
Fuzzy Kappa	0.940	**0.963**	**0.963**	0.955
Industrial area				
Kappa	0.809	**0.827**	**0.827**	0.817
Fuzzy Kappa	0.814	**0.887**	0.885	0.846
Total map				
Kappa	0.965	0.966	**0.969**	**0.969**
Fuzzy Kappa	0.938	0.949	**0.956**	0.954
Kappa*	0.004	0.026	**0.154**	0.149

For each vacant and function land use class, the clumpiness index has been calculated. These results are shown in table 7 for the different maps. The clumpiness index values of all land uses are best for the second calibration. The clusters in the secondly calibrated map resemble the clusters of the land use map best except for the industrial land use class.

Table 7 Calibration results Clumpiness Germany. Bold numbers indicate best resemblance with land use map

	Natural vegetation	Agriculture	Forest	Residential	Industry	Recreation
Germany 2000	**0.708**	**0.700**	**0.727**	**0.612**	**0.597**	**0.561**
RCM 1	0.625	0.685	0.720	0.581	0.481	0.474
RCM 2	0.625	0.685	0.720	0.581	0.481	0.474
RCM 3	0.625	0.685	0.720	0.582	0.481	0.474
RCM 4	0.625	0.685	0.720	0.582	0.481	0.474
RCM 5	0.625	0.685	0.720	0.582	0.481	0.474
Calibration 1A	0.635	0.716	0.739	0.647	0.674	0.621
Calibration 1B	0.675	0.705	0.731	0.627	**0.647**	**0.618**
Calibration 2	**0.678**	**0.698**	**0.729**	**0.607**	0.542	**0.618**

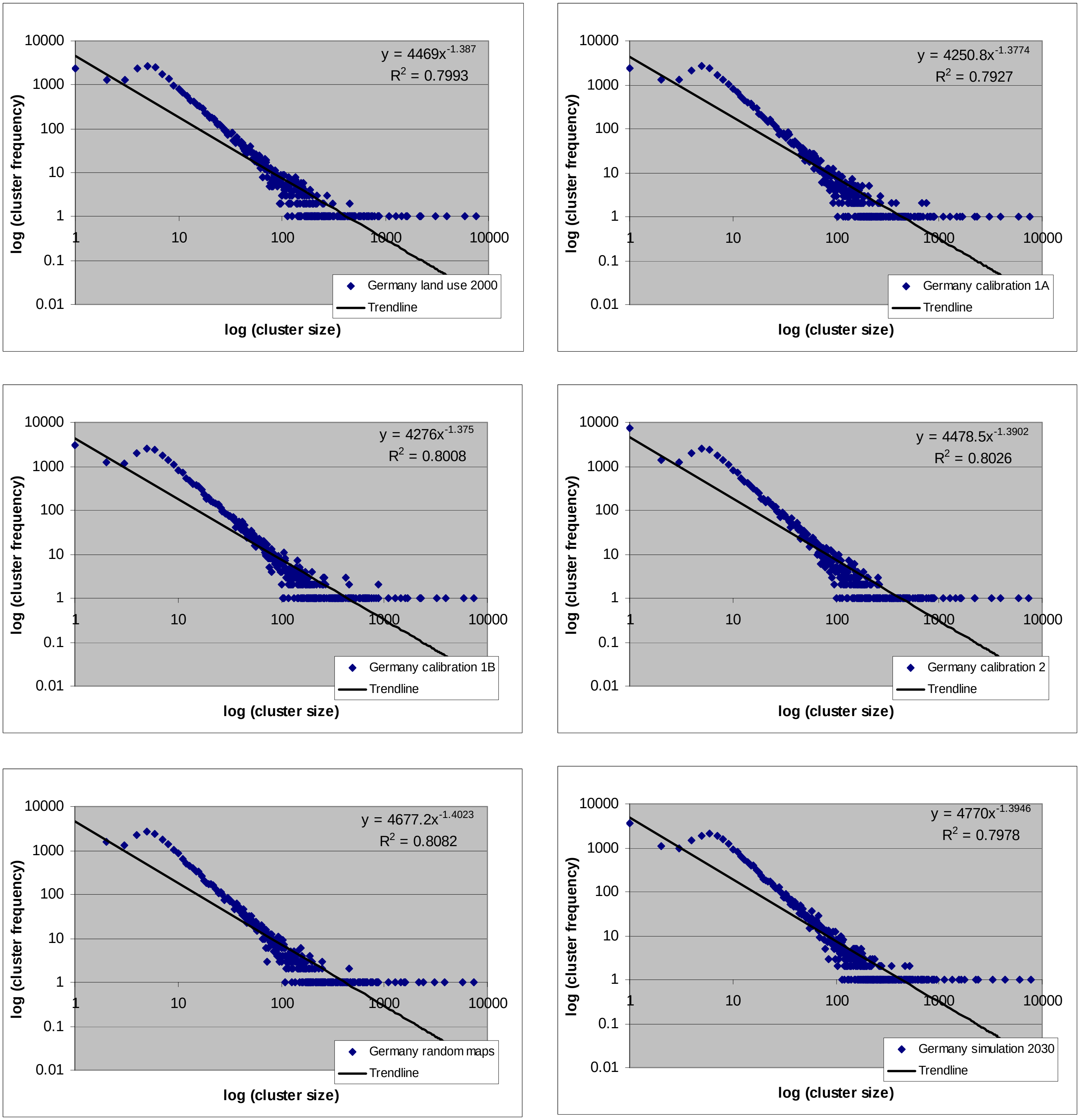


Figure 10: cluster size frequency analyses results for Germany. Graphs represent the analysis of the land use map (top left), the simulation with only the neighbourhood rules (top right), the total first simulation (middle left), the second calibration (middle right), the RCM map (below left) and the simulation of 2030 (below right).

In figure 10, six residential cluster size frequency graphs are shown for the land use map, the three simulations, a RCM map and for a simulation of the year 2030. Here, also the graph's equations and shapes are much alike which means that the simulations have performed well. The RCM map logically has much single cell clusters (not visible in the graph) due to the randomly allocated cells. Furthermore, the two first simulations contain less single cell clusters than the land use map. The slope of the two simulations is less steep, but the slope of the RCM is steeper compared to the slope of the land use map. This implies that the frequency of larger residential clusters declines faster in the two simulations, but less fast in the RCM map compared to the land use map. These differences are however very small.
The cluster size frequency graph and trend line equation for the second calibration are mostly similar with the land use map graph which indicates that the residential land use cluster sizes and frequencies correspond much in this calibration.

4.3.5 Discussion Germany – objective 3

In this chapter, the calibration results of Germany will be discussed.

Kappa values

Here again, calibration 1A (only neighbourhood rules are calibrated here) has the highest Kappa and fuzzy Kappa values indicating that most cells are at exactly the right location. Improving the neighbourhood composition during calibration 2 has not resulted in an improvement of Kappa statistics. As stated before, even if the neighbourhood compositions perfectly correspond with the land use map, the cells do not necessarily have to be at exactly the right location. The Kappa statistics are therefore in this case not sufficient to judge a calibration only based on this Kappa statistic.

Clumpiness index

As in the case of Spain, here the clumpiness index values for all RCM maps are also lower than the values for all land uses in the land use map. The cells do not aggregate much if they are randomly allocated. This results in lower values for the clumpiness index. Both calibrated maps of the first calibration have only higher clumpiness index values than the land use map. The neighbourhood effect is much stronger in these calibrations which results in larger clusters. Again, the clumpiness index values of the second calibration (aimed at improving the neighbourhood compositions of the first calibration) resemble the values of the land use map the best. In this calibration, we have tried to improve the neighbourhood compositions of only the residential and industrial areas. The clumpiness of residential clusters has improved much, but the clumpiness index of industrial areas has even worsened. One of the reasons can be that indeed the neighbourhood composition has improved, but that industrial land use cells have been moved to another location, which changes cluster sizes and thus the clumpiness index.

Cluster size frequency analysis

The shapes of the cluster size frequency analyses graphs correspond much with the land use maps. The RCM map contains more single cell clusters which explain the higher frequency at a size of one cell. Furthermore, calibration 1A and 1B have slightly more, larger clusters which also correspond with the findings of the clumpiness index. In Germany, also very small towns grow, but this is hard to model exactly. This explains why the slope of the land use map is steeper. The differences in these graphs are however only small. The simulation of Germany for the year 2030 seems realistic. The slope is only slightly larger compared to the slope of the land use map which indicates that cluster sizes of the simulation are on average somewhat smaller. Nevertheless, this difference is very small. The second calibration simulates the residential cluster sizes and frequencies very good according to the trend line.

Calibration process Germany

In Germany, we came across another kind of growth pattern than in Spain. Much of the newly established recreational areas are found at places some kilometres outside cities and industrial areas as can be seen in the region of Cologne in figure 11. It is with the present model not possible to allocate these areas exactly at the right location, because numerous locations are suitable for these recreational areas. Furthermore, the growth in residential and industrial areas is spread around the whole country. Also, the small towns (not accessible via available roads) grow and attract some industry in Germany. We therefore have not included accessibility settings in this calibration, because these small towns would always have a disadvantage in accessibility over other towns. It was only possible to model these changes with an equal accessibility factor for all locations in the country. In figure 11, the surroundings of Leipzig are shown. You can obviously see the densely populated area. Even outside the city, the residential area is growing.
The growth in Eastern Germany (the former DDR) for residential and industrial areas is somewhat larger compared to the rest of the country. In the year 1990, the DDR and the 'Bundesrepublik Deutschland' (BRD) form together the new Germany. From that year on, the former DDR develops rapidly to diminish the technological differences of the two parts. Again, different regional growth patterns are hard to model and an in-between solution has to be found.

Germany vs. Spain
In Germany, relatively speaking more cells have changed during the research period compared to Spain (1.7% versus 1.3% cells changed of the total cells in the country). In Spain the growth in residential and industrial areas is mainly concentrated around the larger cities throughout the country, but in Germany the growth of these land uses occurs everywhere throughout the country. In figure 11 on the left site, you can see the simulated area of Leipzig. Compared to Madrid and Valencia (figure 9), the simulation is much alike at first sight. However, the small towns near Leipzig have also grown which is hard to discover. Furthermore, Germany has a much higher average population density (230 people/ km2) compared to Spain (87.2 people / km2), which explains the higher values in the cluster sizes for residential cells for Germany (eurostat, 2008). The range of clumpiness indices for the several land uses correspond reasonably for both countries. All land uses, except forest, are more clustered in Spain compared to Germany which has probably to do with the less dense population in Spain.

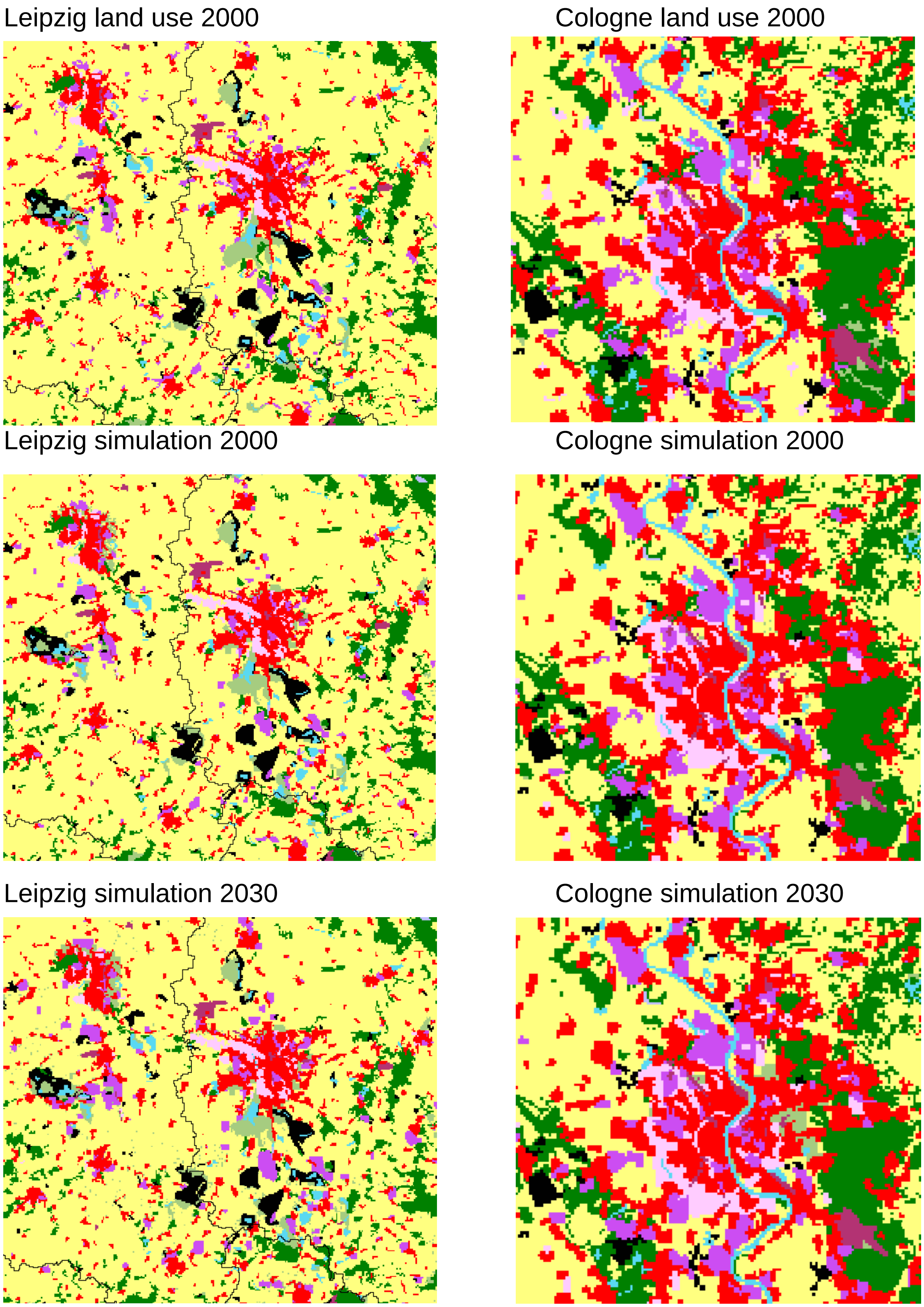


Figure 11: cut-outs simulations Germany. On the left site from top to bottom: Leipzig land use map 2000, Leipzig simulation 2000, and Leipzig simulation 2030. On the right side from up to down: Cologne land use map 2000, Cologne simulation 2000, and Cologne simulation 2030.

4.4 Results sensitivity analyses

In this paragraph, we will show the results of the sensitivity analysis performed. In paragraph 4.4.1, we discuss the results for Spain and in paragraph 4.4.3, the results for Germany are described.

4.4.1 Results sensitivity analyses Spain

In figure 13 and 14, we have plotted the results of the sensitivity analysis for Spain. In figure 13, the logarithm of the enrichment factor has been plotted against the distance for varying attraction and repulsion values. The graphs represent the influence of newly allocated residential cells on already existing residential land use cells.

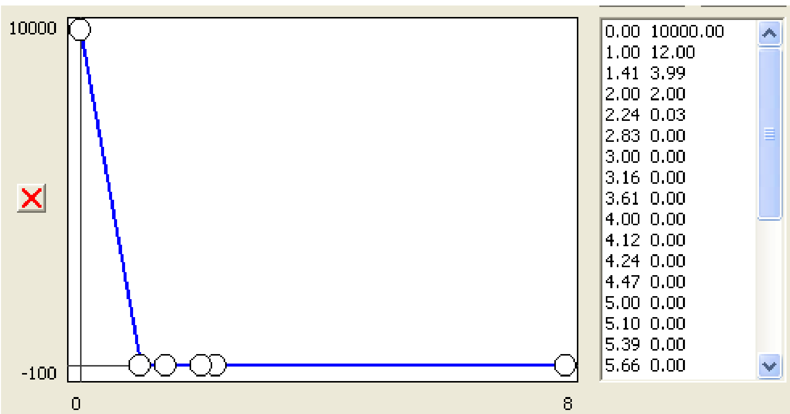


Figure 12: neighbourhood rule that describes the effect of residential cells on other residential cells. The settings in the figure represent the original values of the second calibration (100%).

The different lines represent varying attraction values calculated as percentages of the attraction values of the second calibration as shown in figure 12 (residential 100%). The neighbourhood rule values of residential 10 are 10% of the values for the second calibration, the values of residential 50 are 50% etc. In the sensitivity analysis, all values of the neighbourhood rule are adapted.

The shapes for most lines are very similar and the enrichment factor values differentiate little which indicates that the outcomes are not sensitive. Residential 10% and residential 50% however, deviate much more from the other lines.

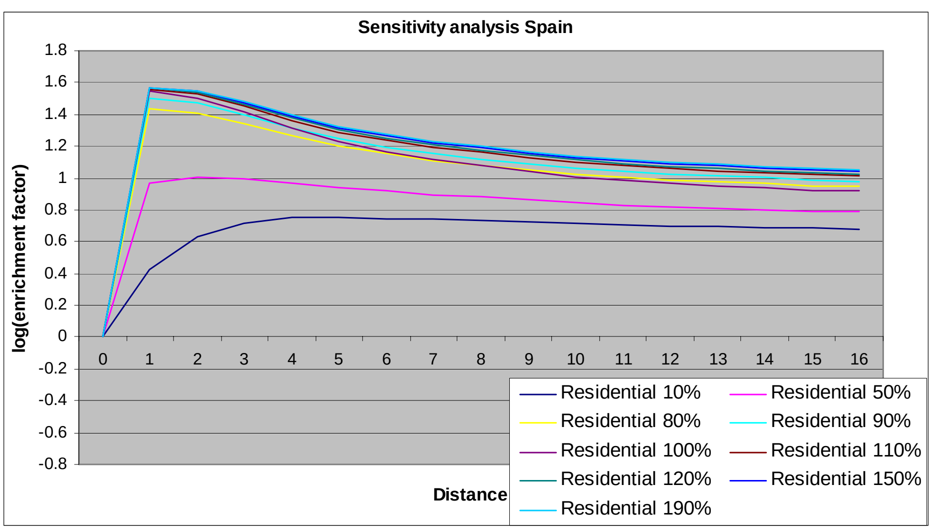


Figure 13: results sensitivity analysis Spain. Figure shows graphs with values 10, 50, 80, 90, 100, 110, 120, 150 and 190% of values from influence graph residential on residential area.

In figure 14, the difference in enrichment factor of the sensitivity analyses and the land use map are plotted. Again, the same pattern arises. The graph of residential 80% lies closest to the x-axis which indicates that the neighbourhood configuration best resemble the land use map. The graphs of residential 10% and 50% have negative values in figure 14 which indicates that the enrichment factor values lie between 0 and 1. As indicated before, enrichment factor values smaller than 1 indicate that in this case residential cells are too little found in the neighbourhood of other residential cells. In the simulated maps of residential 10% and 50%, residential cells are scattered throughout the country and are not clustered at all.

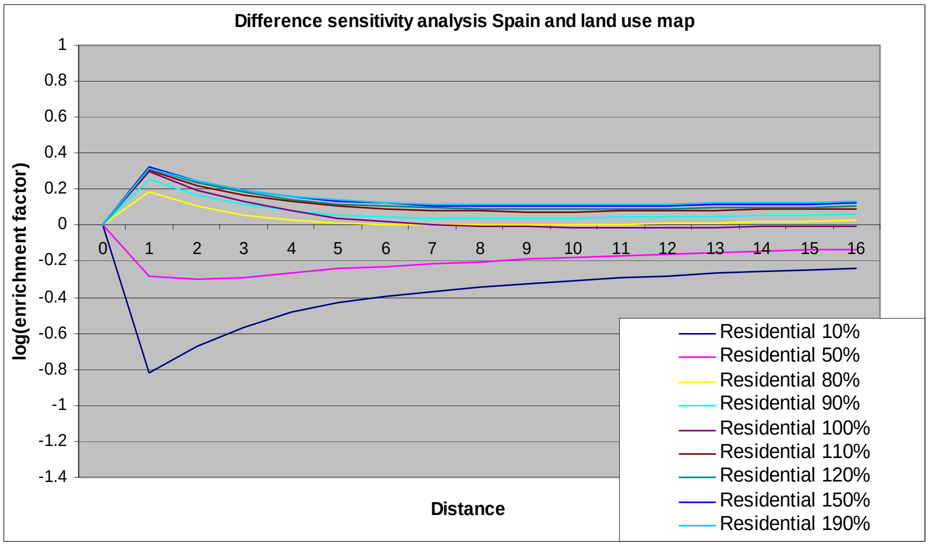


Figure 14: results difference graphs sensitivity analysis Spain. Figure shows difference graphs with values 10, 50, 80, 90, 100, 110, 120, 150 and 190% of values influence graphs from second calibration minus these values from the land use map. The lines represent the effect of residential areas on other residential areas.

In table 8, the results of the Kappa statistics and clumpiness index values are shown for all variations of the sensitivity analysis. The kappa values and the clumpiness index values increase if the attraction increases. However, the residential fuzzy Kappa statistic of residential 190% is lower than the value of residential 150%, but this difference is very small. The residential clusters of residential 80% best resemble the land use clusters.

Table 8: overview Kappa statistics and clumpiness index values for all sensitivity simulations Spain

	Kappa total	**Kappa residential**	**FKappa total**	**Fkappa residential**	**Clumpiness**
Residential 10%	0.944	0.858	0.908	0.876	0.571
Residential 50%	0.944	0.860	0.909	0.885	0.598
Residential 80%	0.945	0.868	0.910	0.910	**0.659**
Residential 90%	0.945	0.870	0.910	0.916	0.675
Residential 100%	0.945	0.872	0.911	0.920	0.688
Residential 110%	0.945	0.872	0.911	0.921	0.692
Residential 120%	0.945	0.872	0.911	0.922	0.695
Residential 150%	**0.945**	**0.873**	**0.911**	**0.922**	0.698
Residential 190%	0.945	0.873	0.911	0.921	0.699
Land use 2000					**0.661**

In figure 15, three examples of the cluster size frequency graphs are shown. We have plotted residential 10, residential 100 and residential 190. The other graphs can be found in Appendix VII. With increasing attraction values (from residential 10 to residential 190), the slope of the trend line decreases and the value at x=0 also decreases. This indicates that less small and single cell residential clusters and more large clusters appear if the attraction increases.

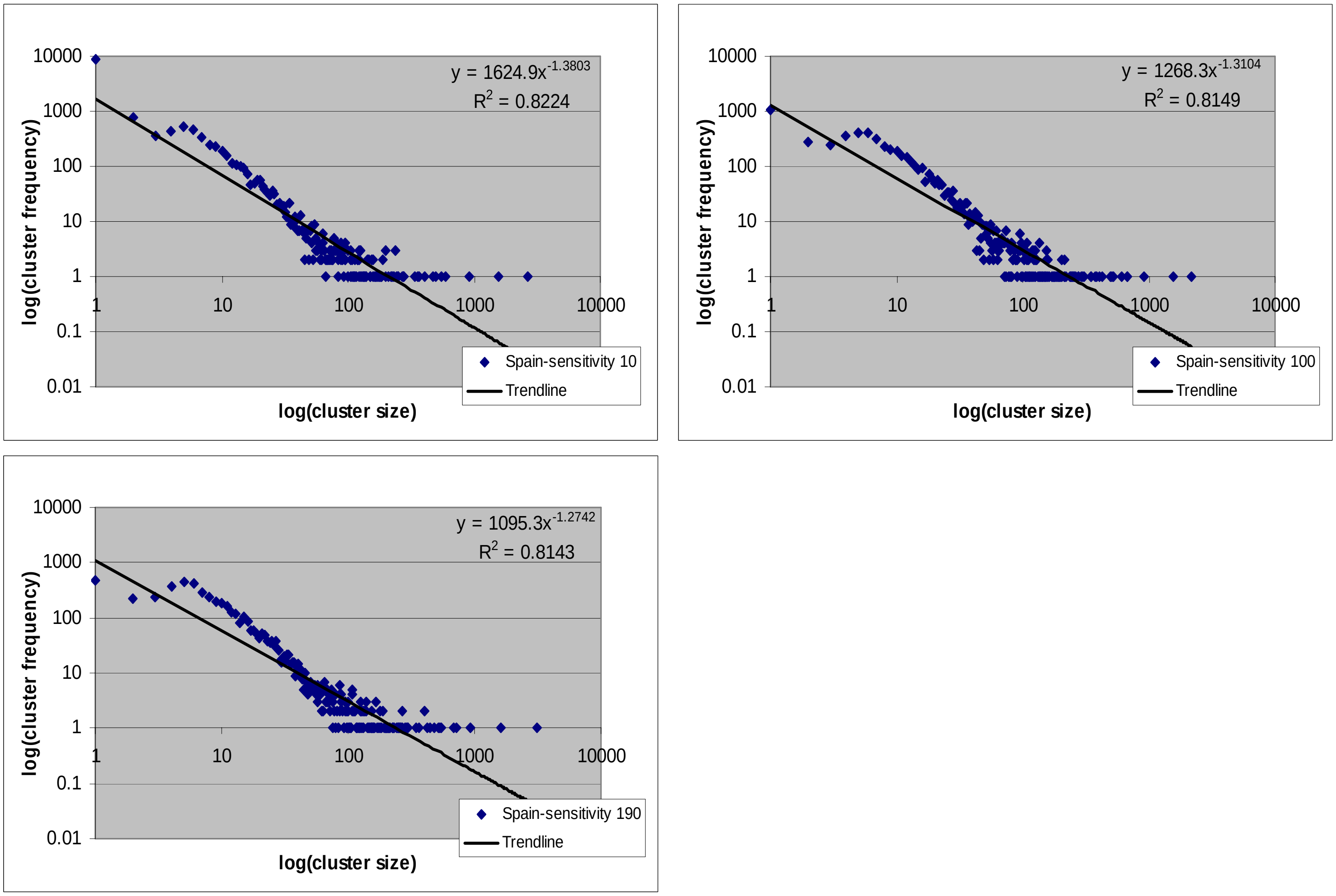


Figure 15: cluster size frequency distribution sensitivity analysis Spain. Spain sensitivity analysis with values 10% of calibration two (top left), Spain sensitivity analysis with calibration two values (top right) and sensitivity analysis with 190% values of calibration two (bottom left).

4.4.2 Discussion sensitivity analysis Spain

The outcomes show that the enrichment factors are not influenced much by changes made in the influence graphs. At very low attraction values, the enrichment factor drops. The Kappa and clumpiness index values increase with increasing attraction values due to stronger clustering. Residential 10 and 50 show larger differences for the enrichment factors and clumpiness index, but the Kappa statistics remains quite constant. The relative amount of changed residential cells in Spain is very small and therefore the wrongly placed residential cells do not account much for a change in the Kappa statistic. Even the amount of changed residential cells relative to the total number of residential cells is not large and therefore the Kappa residential value does not change a lot. The clumpiness index value of residential 80% is closest to the value of the land use map, even better than the value for the second calibration. However, the influence of other land uses at residential areas in the second calibration can also influence the neighbourhood configuration. Therefore, the parameter settings of residential 80% do not necessarily mean a better clumpiness index value in the second calibration. The increasing attraction values result in more larger and less smaller residential clusters.
In short: the enrichment factor does not seem to be influenced much by varying attraction values. If the attraction values become too small, the enrichment factor drops strongly. Also, in

the case of residential 10% and 50% the attraction is too small for clusters to be formed. Residential areas are scattered throughout the simulated maps.

4.4.3 Results sensitivity analyses Germany

In figure 16 and 17, we have plotted the results of the sensitivity analysis for Germany. In figure 16, the logarithm of the enrichment factor has been plotted against the distance for varying attraction and repulsion values. The graphs represent the influence of newly allocated residential cells on already existing residential land use cells. The different lines represent varying attraction values calculated as percentages of the attraction values of the second calibration (residential 100%).

The results have similarities with those of Spain; for all variations, except residential 10% and 50%, the shapes and values do not deviate much from each other. The variations seem a bit larger than those of Spain.

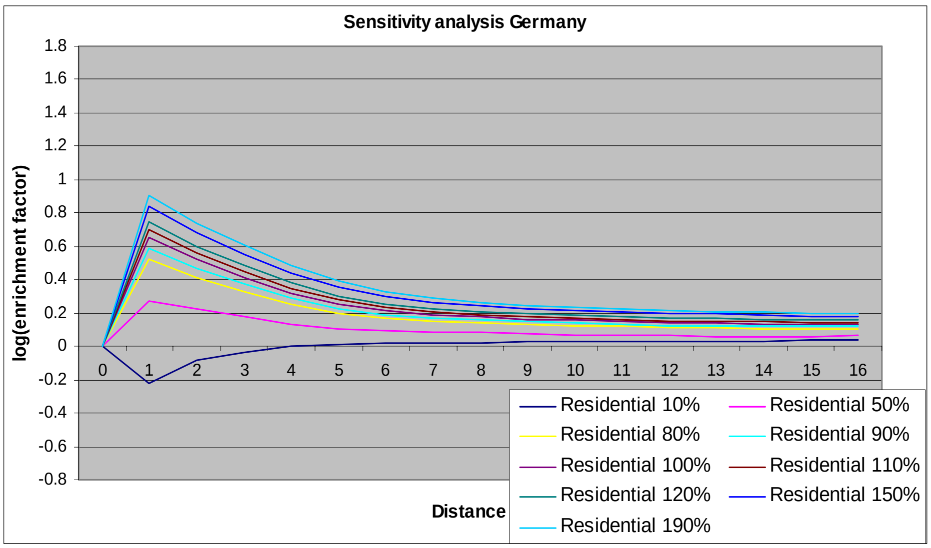


Figure 16: sensitivity analysis Germany. Figure shows graphs with values 10, 50, 80, 90, 100, 110, 120, 150 and 190% of values from influence graph residential on residential area.

In figure 17, we plotted the difference of the enrichment factors for the sensitivity graphs and the land use map, similar to figure 7. The same pattern as in the previous graph occurs; most lines have the same shape and deviate not much from each other, except for the residential 10% and residential 50% lines.

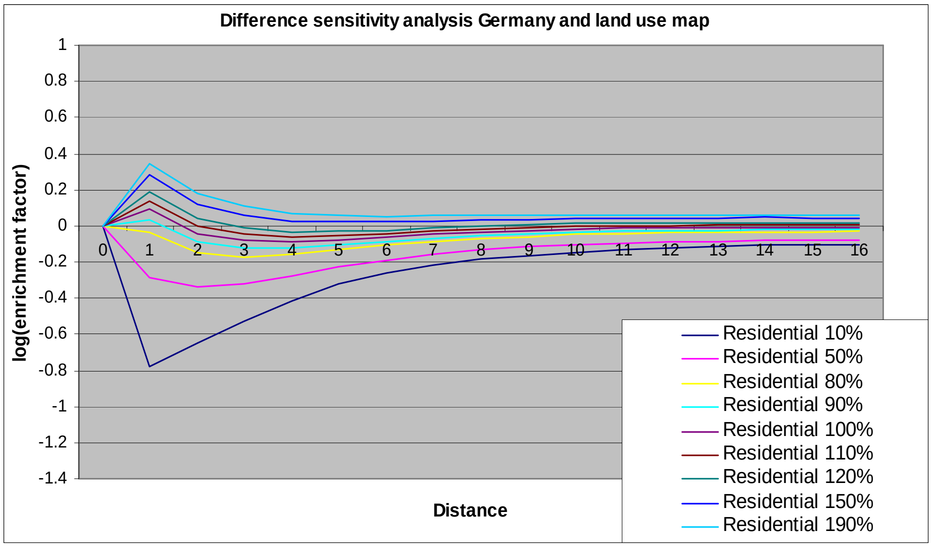


Figure 17: difference graph sensitivity analysis Germany. Figure shows difference graphs with values 10, 50, 80, 90, 100, 110, 120, 150 and 190% of values influence graphs from second calibration minus these values from the land use map. The lines represent the effect of residential areas on other residential areas.

In table 9, Kappa, fuzzy Kappa and clumpiness index values are shown for all sensitivity graphs. The more the attraction values increase, the higher the values for the Kappa statistics and clumpiness index become. The highest values for both Kappa statistics are therefore found for residential 190%. The clumpiness index which best resembles the value for the land use map is the residential 110% graph in stead of the residential 100%.

Table 9: overview Kappa statistics and clumpiness index values for all sensitivity simulations Germany

	Kappa total	**Kappa residential**	**FKappa total**	**Fkappa residential**	**Clumpiness**
Residential 10%	0.725	0.065	0.578	-0.194	0.059
Residential 50%	0.969	0.953	0.952	0.947	0.590
Residential 80%	0.969	0.954	0.953	0.952	0.600
Residential 90%	0.969	0.954	0.953	0.953	0.603
Residential 100%	0.969	0.954	0.954	0.955	0.607
Residential 110%	0.969	0.954	0.954	0.957	**0.611**
Residential 120%	0.969	0.955	0.954	0.958	0.614
Residential 150%	0.969	0.955	0.955	0.962	0.623
Residential 190%	**0.969**	**0.955**	**0.956**	**0.964**	0.631
Land use 2000					**0.612**

In figure 18, we have plotted two examples of cluster size frequency analysis graphs. The left graph shows the residential cluster sizes and frequency of the residential 10% simulation and the right graph shows the distribution for residential 100% (second calibration). The graphs for the other sensitivity simulation are very much similar to the graph of residential 100% and are not shown here, but can be found back in Appendix VIII. In the left graph, we can obviously see that the clustering of residential cells has strongly decreased due to the weak attraction of residential on residential land use cells.

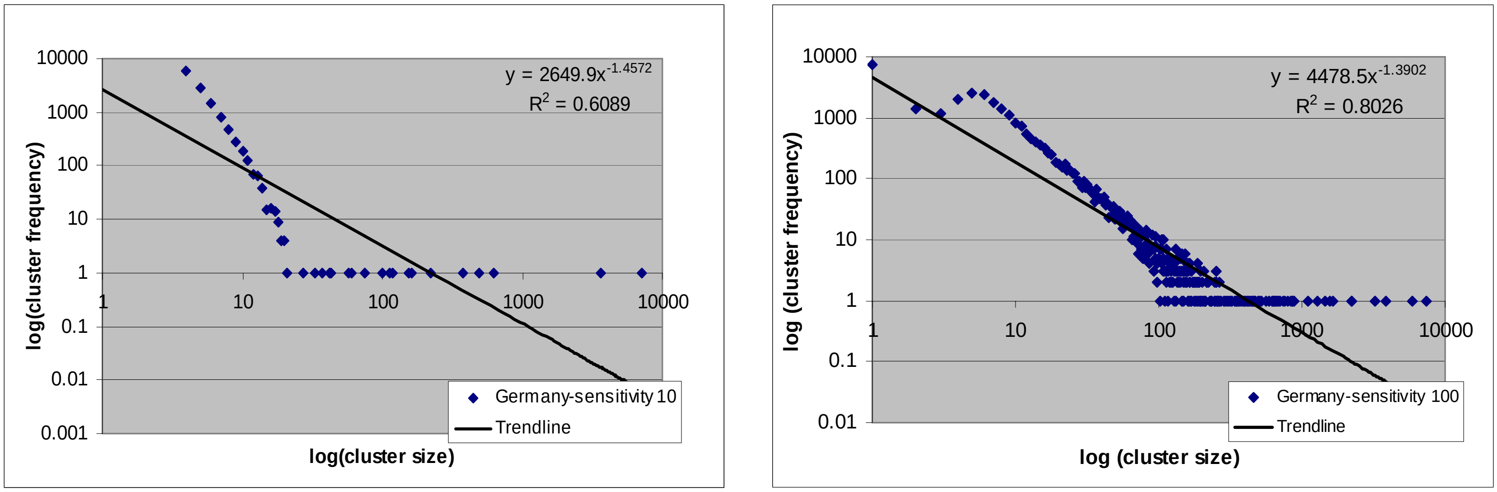


Figure 18: cluster size frequency distribution sensitivity analysis. Germany sensitivity analysis with values 10% of calibration two (left) and Germany sensitivity analysis with calibration two values (right)

4.4.4 Discussion sensitivity analysis Germany

Again, the sensitivity analysis shows that the enrichment factor values are robust. Only at very low attraction values (10% and 50% of the original values), the enrichment factor drops strongly.

The Kappa and clumpiness index values increase with increasing attraction values. The more residential cells attract other residential cells, the larger the residential clusters and thus the clumpiness index values will be. Also, the Kappa values increase with increasing attraction values. The large residential clusters contain much cells placed at the right location resulting in high Kappa values. The Kappa values stay very stable at increasing attraction values. Residential 10% is an exception of this rule however, because the Kappa values and clumpiness index value are much lower compared to the other graphs. At this point, newly placed residential cells are not attracted anymore by other residential cells and already placed residential cells can also be replaced due to the lower inertia value which results in many single cell residential clusters. This effect can also be seen at the cluster size frequency distribution at figure 18.

In short: the enrichment factors are not very sensitive for varying attraction values. Only at very small attraction values, the enrichment factors and accompanied statistics deviate to a large extent.

5. Conclusions

In this chapter, we will summarize the main conclusions of this research based on the research objectives and research questions.

Research objectives and questions:

1. To determine the land use attraction and repulsion effects present between 1990 and 2000 in both Germany and Spain.
    a. Which attraction and repulsion effects exist and how do they develop over increasing distance?
    b. What are the differences of the attraction and repulsion effects in the two regions?

In the land use maps of 2000, new residential and industrial areas in both Spain and Germany are repulsed by natural vegetation and forest and are attracted by already existing industrial, residential and recreational areas. Agricultural areas and water have almost no influence on industrial and residential areas.
The attraction and repulsion effects of both countries correspond reasonably. In other words, similar land uses have the same type of influence on residential and industrial areas. However, the strength of the attraction and repulsion effects are different. Therefore, the neighbourhood rules should be adapted for each region separately. No common neighbourhood rules can be created for all regions, but the shape of the neighbourhood rules are often similar.

2. To compare the neighbourhood effects of the land use map and a simulated map of both regions.
    a. What are the differences in the neighbourhood effects of the simulated map and the land use map and can they be explained?

The simulated map based on an expert calibration performs much better than the random constraint match. The neighbourhood configurations of the calibrated map are however slightly different compared to the land use map. Only at larger distance (> 1km) the configurations are similar. Although based on expert knowledge, the neighbourhood configuration of the calibrated map is not exactly similar to the land use map. Especially, the model's inertia values appeared to high and influenced the enrichment factor strongly. However, not all differences can be diminished due to classification errors and restricted data availability.

3. To find out whether we can improve the calibration process with the neighbourhood relations found in the real maps.
    a. Can the calibration be improved in both countries with the gained neighbourhood effect knowledge?
    b. Can the results of this research be used in the automation of the calibration procedure?

We have found that the neighbourhood configuration of a calibration solely based on expert knowledge already corresponds well with the configuration found in the land use maps. With the aid of the enrichment factor and the attraction and repulsion graphs based on that, we have even decreased the differences between the land use map and the calibrated map within the second calibration. Furthermore, we found that the global patterns and shapes of the attraction and repulsion graphs of the neighbourhood configuration do have similarities for both countries, but the values for Spain are significantly higher than for Germany due to the relative larger amount of changed cells. Also, the overall Kappa and Fuzzy kappa values are

mostly highest after the second calibration (0.945, 0.911 and 0.969, 0.954 for Kappa and Fuzzy Kappa values for Spain and Germany respectively). For the residential and industrial land use class separately however, the Kappa values for the second calibration are lower than the two other calibrations. The differences for residential areas are very small (Spain: 0.878, 0.871 0.872 and Germany: 0.956, 0.955, 0.954 for calibration 1A, 1B and 2 respectively), but the differences for industrial areas are larger (Spain: 0.653, 0.651, 0.647 and Germany: 0.827, 0.827, 0.817 for calibration 1A, 1B and 2 respectively). As stated before, an improvement of the neighbourhood configurations does not mean that the cells have to be at exactly the right location. The neighbourhood configuration has strongly improved during the second calibration, but the cells are not placed exactly at the right location.
Furthermore, the clumpiness index is better able to demonstrate the improvements made in the neighbourhood configuration. For both countries, the shapes of five out of six land uses best resemble the real shapes after the second calibration. In Germany, the second calibration has even resulted in much better values compared to the first calibration.
Also, the cluster size frequency analyses show that the residential cluster sizes and frequencies of the second calibration best correspond with those of the land use map. The neighbourhood configurations are not very sensitive for changes made in the neighbourhood rules. In the next chapter, we will discuss the possibilities of an automation of this method.

6. Discussion

For an extensive discussion of the results, we refer to the discussion paragraphs in chapter 4. In chapter two we have described some examples of researches that investigated methods for improving the calibration of transition rules. In this research, we try to contribute to this process by learning more about neighbourhood effects on land use change. We have used the enrichment factor, which is an example of a spatial metric, to do so. The enrichment factor is very useful to improve the neighbourhood configurations and the land use cluster shapes and frequencies in the calibration procedure. We have calibrated the model with as main goal to be able to model the land use development patterns (cluster shapes) as good as possible. The use of the enrichment factor during the calibration procedure has definitely improved the land use clusters shapes and frequencies. We have however come across several issues that have to be taken into account for future research. We will discuss them in this chapter.

Other researches results
In Verburg et al. 2004, the author also creates attraction and repulsion graphs. The line shapes roughly correspond with our findings, but the strength of the effects is much smaller at Verburgs research which can be assigned to the geographically different research area and the amount of changed land use during the research period.
Hagoort et al. 2008 is actually the only other researcher that has run an improved simulation (see chapter 2). He also improved his calibration results with the aid of the enrichment factor, but he did not describe how exactly he has done this. He used the fuzzy Kappa as a measure to indicate the performance of his calibration. This method is however pixel based; he did not use any measures based on shapes or frequencies of land use clusters. However, our results do partly comply; for both researches the overall fuzzy Kappa value is highest in the final calibration. Hansen (2008) has not published yet about his calibration results at the moment of writing this thesis.

Calibration of CA; not only based on transition rules
In this research, we have looked at one option to automate the calibration of transition rules. However, as shown before, a CA-based land use model exists of more components than only the transition rules. The calibration results also depend on the other components as shown in figure 19. We will shortly go through each CA component and discuss their influence on the calibration process.

The time scale differs in every CA-based model, but a time step of 1 year is often used. However, a yearly update of land use data is not always available, so often the used land use data has only been updated once in several years or less. Hansen (2008) has shown that the neighbourhood configuration improves if a yearly updated land use map is used. Moreover, the neighbourhood effects found in this research, and calculated during a 10 year period, can not be used directly as input for the Metronamica model. The Metronamica land use change model uses a time scale of one year. Due to the non-linearity of the neighbourhood effects, they cannot directly be used by the model.

The raster cell space also influences the calibrations outcomes. Of course, the size of the total research area influences the calibration result. A division of the Netherlands in north and south for example has resulted in better calibration results compared to the calibration of the whole Netherlands (Verburg et al. 2004). Furthermore, the spatial resolution influences the calibration. Ménard and Marceau (2005) have assessed the sensitivity and impact of changing spatial resolution on model outcomes.

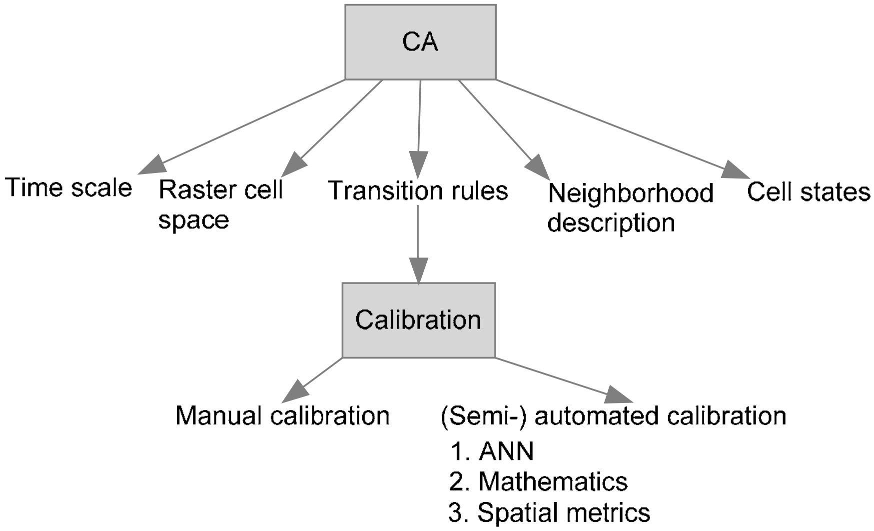


Figure 19: context of automatic calibration methods for CA-based land use change models

The Metronamica model, used for the calibrations, uses a circular neighbourhood type and a neighbourhood size of 8 cells. These factors also differ per model. Kocabas and Dragicevic (2006) have assessed the influence of neighbourhood size and type on model outcomes. We have analysed the neighbourhood effect up to a distance of 16 cells (figures 6 and 7). It appeared that the neighbourhood effect was very small for all land uses at distances larger than 8 cells. A neighbourhood size of 8 cells in the Metronamica model seems therefore sufficient.

The cell states are also very diverse in the different CA-models. Each model has its own land use classification. The classification is often based on remotely sensed data. One cell often represents a certain land use that is most present in that area. Sometimes, classification errors occur due to the small differences. Residential areas are often confused with industrial and commercial units and forest and natural vegetation can also look very similar. These classification errors can influence calibration results.

As stated before, transition rules suitable for every application do not exist. One major advantage of the enrichment factor is that it directly measures neighbourhood configurations based on land use maps or simulated maps. However, the enrichment factor values also differ per region and per spatial resolution (Verburg et al. 2004). It is very important that for each calibration, the enrichment factor values are calculated again.

Data restrictions and method drawbacks

In past times, land use change decisions were mainly restricted or encouraged by the physical environment such as soil characteristics, climate and distance from natural resources etc. Nowadays, the means to alter the physical environment have increased strongly, but policy measures have an increasing impact on the allocation of changing land use nowadays. Human made decisions are not always predictable and do not always depend on soil suitability, zoning and road networks, and are therefore not easily modelled. Furthermore, data availability can restrict the quality of the outcomes. In this case, no zoning information was available about policy decisions for example. Also, as discussed earlier, classification errors can cause irregularities in the outcomes. Forest and natural vegetation, and residential area and industry are sometimes difficult to distinguish at satellite based data and can be classified wrongly.

Furthermore, not all relations described with the enrichment factor are causally related. Some of the neighbourhood effects are indirect results of other interactions.

With our method, we were not able to statistically test the differences in attraction and repulsion between the neighbourhood configurations of the calibrated map and the land use map. The Neighbourhood Analyzer has not yet been programmed to calculate standard deviations and therefore only a visible assessment of the differences can be made. We used however a number of statistics to measure the performance differences and they indeed indicate that differences exist. In future researches, the standard deviations of the calculated enrichment factors can be used in t-tests to indicate changes between land uses and countries.

Recommendations

The results of this research do indicate that the land use cluster size and frequency can be improved in the calibration using the method described in this thesis, although it is far too time intensive.

However, an automation of the research steps performed here to improve the neighbourhood configuration is possible and would certainly decrease the time extent. One important remark should be made about his automation. We only worked with effects on the residential and industrial land use and it appeared that a change in effects of one land use did not or only minimally influenced the other land use. It is however not clear if the effects of all other land uses influence each other. An automation of the procedure will become much more difficult if the land uses interact strongly. Furthermore, only land uses with a certain amount of cells should be taken into account in this method. The neighbourhood effect of a land use class with too little cells is very sensitive for changes and not easily modelled.

The models used to simulate these changes are mostly used to explore future development scenarios and policies. An exploration usually involves an accepted amount of uncertainty, but on the other hand a high amount of causality (Ridder et al. 2007). In the introduction, we have argued for a more empirically based calibration method for this kind of land use change models in which we have partly succeeded. On the one hand, we have come up with measured over and underrepresentations of land uses in each others neighbourhood. These effects are visually assessed, and the differences between them are validated by several statistics. On the other hand however, we would want to test whether or not the neighbourhood interactions of the land use map significantly differ from the three calibrations. In a next research, this should be investigated. Furthermore, the data we have used are only measured once in ten years. For a future research, it is of importance that we use (remotely sensed) data for each year separately. Then, we are better able to understand neighbourhood interactions year by year and it is better possible to use these results directly in the calibration procedure.

An automated and causally based calibration procedure is still not realizable, but we are again a step further in that direction. One of the reasons is that common rules for calibration do not exist. The neighbourhood interaction rules differ per region, per time period and per resolution, although similarities are present. With this research, we have made clear that the neighbourhood configurations certainly can be improved by means of the enrichment factor. A future automated calibration procedure should take this fact into account.

Glossary

Enrichment factor: a measure that indicates whether a certain land use is over or-under represented in the neighbourhood of a cell compared to the average neighbourhood of the total map (see equation 1).

Neighbourhood configuration: locations and type of land uses in the neighbourhood of a cell. The neighbourhood configuration differs per distance chosen for the neighbourhood.

Neighbourhood effect: the attraction or repulsion effect of surrounding cells which eventually causes a change in cell status (type of land use) of the centre cell.

Neighbourhood of a land use cell: the cells surrounding a certain land use cell in a raster land use map. Most known neighbourhood is the so called ‘Moore neighbourhood’ which is a square neighbourhood around a central cell. In this research, we have used a circular neighbourhood function.

Neighbourhood rule = spline = influence graph: describes the attraction and repulsion of a set of land uses at varying distances (see figure 4).

References

Batten, D.F. and D.E. Boyce. 1986. Spatial Interaction, Transportation and Interregional Commodity Flow Models. In: *Handbook of Regional and Urban Economics*. Vol. 1, pp. 357-406 ed. P. Nijkamp, Amsterdam.

Batty, M. 1976. *Urban Modelling: Algorithms, Calibrations, Predictions*. Cambridge: Cambridge University Press

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

Briassoulis, H. 2000. *Analysis of land use change: theoretical and modelling approaches.* Regional research institute, West Virginia Universtiy. http://www.rri.wvu.edu/WebBook/Briassoulis/contents.htm [last visited: November 2008]

Brown, D.G., Goovaerts, P., Burnicki, A., Li, M.Y. (2002). Stochastic simulation of land-cover change using geostatistics and Generalized Additive Models. *Photogrammetric Engineering and Remote Sensing.* Vol. 68, pp. 1051-1061.

Congalton, R.G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment.* Vol. 37, pp. 35-46.

Engelen, G., White, R. and Uljee, I. (2002). The MURBANDY and MOLAND models for Dublin. Final report, RIKS.

EEA. (2008). European Environmental Agency. Corine land cover 2000. http://dataservice.eea.europa.eu/dataservice/metadetails.asp?id=1008 [last visited November 2008].

Eurostat, Statistical Office of the European Communities (2008). http://epp.eurostat.ec.europa.eu/portal/page?_pageid=1073,46870091&_dad=portal&_schema=PORTAL&p_product_code=REG_D3DENS [last visited: November 2008].

Fischer, M. and P. Nijkamp. 1993. "Design and Use of Geographic Information Systems and Spatial Models." In *Geographic Information Systems, Spatial Modelling, and Policy Evaluation*. eds. M. Fischer and P. Nijkamp, pp. 3-13. Berlin: Springer-Verlag.

GISCO. 2009. http://epp.eurostat.ec.europa.eu/portal/page?_pageid=2254,62148876,2254_62153824&_dad=portal&_schema=PORTAL

Hagen-Zanker, A. and Lajoie, G. (2008) Neutral models of landscape change as benchmarks in the assessment of model performance. *Landscape and Urban planning* 86 (3-4), 284 – 296

Hagen-Zanker, A., Straatman, B., Uljee, I. (2005). Further developments of a fuzzy set map comparison. *International journal of geographical information science*, vol. 19, issue 7, pp. 769-785.

Hagoort, M., Geertman, S., and Ottens, H. (2008). Spatial externalities, neighbourhood rules and CA land-use modelling. *Annals of regional science,* vol. 42, pp. 39-56.

Hansen, H.S. (2008). Quantifying and Analysing Neighbourhood Characteristics Supporting Urban Land-Use Modelling. Lecture Notes in Geoinformation and Cartography, the European Information Society, pp. 283-299.

Hill, D.M. 1965. "A growth allocation model for the Boston region." *Journal of the American Institute of Planners* 31: 111-120.

Junfeng J (2003). Transition rule elicitation for urban cellular automata models, Case study: Wuhan, China. Enschede, International Institute for Geo-Information Science and Earth Observation.

Lewis, D.J., Plantinga, A.J. (2004) Policies to reduce forest fragmentation: combining econometric models with GIS-based landscape simulations. Oregon state University, Department of Agricultural and Resource Economics.

Li, X., and Yeh, A. G. (2001). Calibration of cellular automata by using neural networks for the simulation of complex urban systems. *Environment and Planning A*, vol. 33, pp. 1445–1462.

McGarigal, K., Marks, B. (1995). FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. Department of Natural Resources Conservation; University of Massachusetts.
http://www.umass.edu/landeco/research/fragstats/documents/Metrics/Contagion%20-%20Interspersion%20Metrics/Metrics/C115%20-%20CLUMPY.htm [last visited 30 October 2008].

Ridder, N. de, Ittersum, M.K. van, Keulen, H. van, Haan, J.J. de, Rossing, W.A.H., Schipper, R.A., Claassen, G.D.H., Hendriks, T.H.B., Stoorvogel, J.J. (2007). Quantitative Analysis of Land Use Systems (QUALUS). Plant Sciences. Wageningen Universiteit

RIKS, 2008. LUMOCAP. European Commission, DG-RTD / Contract: SSPE-CT-2005-006556
http://www.riks.nl/projects/LUMOCAP

Smith, T.E. (1976). Spatial discounting and the gravity hypothesis. *Regional Science and Urban Economics*, vol. 6, pp. 331–356.

Smith, D.M. (1977). Human geography: a welfare approach. Edward Arnold, London.
Stoorvogel, J.J., Schipper, R.A. and Jansen, D.M. 1995. "USTED: A Methodology for a Quantitative Analysis of Land Use Scenarios." *Netherlands Journal of Agricultural Science* 43, 5-18.

Straatman, S., Hagen, A., Power, C., Engelen, G., and White, R. (2001). The Use of Cellular Automata for Spatial Modelling and Decision Support in Coastal Zones and Estuaria. Land Water Milieu Informatie Technologie, LW 139.

Straatman, B., White, R. and Engelen, G. (2004). Towards an Automatic Calibration Procedure for Constrained Cellular Automata, *Computers, Environment and Urban Systems*, vol. 28, pp. 149-170.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, vol. 46(2), pp. 234-240.

Torrens, P.M. (2000). How cellular models of urban systems work: 1. Theory. Centre for Advanced Spatial Analysis, University College London, Paper 28.

Van Delden, H., van Vliet, J., Muhammad, S. (2007). Practical exercises for using Scendes. RIKS, Maastricht.

Van Vliet, J. (2009) Assessing the accuracy of changes in spatial explicit land use models. Submitted for to the 12th AGILE International conference on Geographic Information Science, June 2nd – 5th 2009 Hannover, Germany

Torrens, P. M., & O'Sullivan, D. (2001). Editorial: cellular automata and urban simulation: where do we go from here? *Environment and Planning B*, vol. 28, pp. 163–168.

Verburg, P.H, Soepboer, W., Veldkamp, A., Limpiada, r., Espaldon, v. and Mastura, S. (2002). Modelling the spatial dynamics of regional land use: the CLUE-S model. *Environmental Management*, vol. 30, pp. 391-405.

Verburg, P.H, de Nijs. T.C.M., van Ritsema Eck, J., Visser, H., de Jong, K. (2004). A method to analyse neighbourhood characteristics of land use patterns. *Computers Environment and Urban System*, Vol. 28(6), pp. 667–690.

Verburg, P.H, van Ritsema Eck, J., de Nijs, T.C.M., Visser, H. and de Jong, K. (2004b). Determinants of land-use change in the Netherlands. *Environment and Planning B: Planning and Design*, Vol. 31, pp. 125-150.

White R, Engelen G. (1993). Fractal urban land use patterns: a cellular automata approach. *Environmental Planning A*, vol. 25, pp. 1175–1199.

White, R., and Engelen, G. (1997). Cellular automata as the basis of integrated dynamic regional modelling. *Environment and Planning B*, vol. 24, pp. 235–246.

White, R., & Engelen, G. (2000). High-resolution integrated modelling of the spatial dynamics of urban and regional systems. *Computers, Environment and Urban Systems*, vol. 24, pp. 383–400.

White, R. (2006). Pattern based map comparisons. *Journal of Geographical Systems.* Vol. 8, pp. 145-164.

Wu, F. (1998). SimLand: a prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rule. *International Journal of Geographical Information Science*, vol. 12, pp. 63–82.

Appendices

Appendix I: Reclassification scheme for both initial and final map

Table 10: reclassification scheme for initial and final map based on the Corine Land Cover maps (CLC) for both Spain and Germany

Value CLC	CLC 1990	Reclassification initial/final map	Value initial/final map
1	Continuous urban fabric	Residential area	1
2	Discontinuous urban fabric	Residential area	1
3	Industrial or commercial units	Industrial and commercial units	4
4	Road and rail networks and associated land	Infrastructure	8
5	Port areas	Infrastructure	8
6	Airports	Infrastructure	8
7	Mineral extraction sites	Mineral extraction and dump site	7
8	Dump sites	Mineral extraction and dump site	7
9	Construction sites	Mineral extraction and dump site	7
10	Green urban areas	Recreation	5
11	Sport and leisure facilities	Recreation	5
12	Non-irrigated arable land	Agricultural area	3
13	Permanently irrigated land	Agricultural area	3
14	Rice fields	Agricultural area	3
15	Vineyards	Agricultural area	3
16	Fruit trees and berry plantations	Agricultural area	3
17	Olive groves	Agricultural area	3
18	Pastures	Agricultural area	3
19	Annual crops associated with permanent crops	Agricultural area	3
20	Complex cultivation patterns	Agricultural area	3
21	Land principally occupied by agriculture …	Agricultural area	3
22	Agro-forestry areas	Agricultural area	3
23	Broad-leaved forest	Forest	2
24	Coniferous forest	Forest	2
25	Mixed forest	Forest	2
26	Natural grasslands	Natural vegetation	0
27	Moors and heath land	Natural vegetation	0
28	Sclerophyllous vegetation	Natural vegetation	0
29	Transitional woodland-shrub	Natural vegetation	0
30	Beaches, dunes, sands	Natural vegetation	0
31	Bare rocks	Natural vegetation	0
32	Sparsely vegetated areas	Natural vegetation	0
33	Burnt areas	Natural vegetation	0
34	Glaciers and perpetual snow	Natural vegetation	0
35	Inland marshes	Wetlands	6
36	Peat bogs	Wetlands	6
37	Salt marshes	Wetlands	6
38	Salines	Wetlands	6
39	Intertidal flats	Wetlands	6
40	Water courses	Water	9
41	Water bodies	Water	9
42	Coastal lagoons	Water	9
43	Estuaries	Water	9
44	Sea and ocean	Water	9
48	NODATA	Out of modelling area	10
49	UNCLASSIFIED LAND SURFACE	Natural vegetation	0
50	UNCLASSIFIED WATER BODIES	Water	9

Values initial and final maps:

0. Natural vegetation = vacant class
1. Residential area = function class
2. Forest = function class
3. Agricultural area = function class
4. Industrial and commercial unit = function class
5. Recreation = function class
6. Wetland = feature class
7. Mineral extraction and dump site = feature class
8. Infrastructure = feature class
9. Water = feature class
10. Out of modelling area = feature class

Appendix II: reclassification scheme transport networks

The transport network data is extracted from the GISCO database which is also used in the Lumocap project. A reclassification has been applied according to the following scheme:

Table 11: reclassification scheme transport networks

Old class GISCO	Class after reclassification	Raster value
Unknown	Planned road	0
Motorway	Motorway	1
Motorway, European	Motorway	1
Dual carriageway road	Expressway	2
Dual carriageway road, European	Expressway	2
Other road	Primary road	3
Other road, European	Primary road	3
Car ferry	Car ferry	4

In the old GISCO class ‘unknown’, it appeared that most roads did not exist yet, but are planned to be built. The roads that did already exist, but still have been classified as ‘unknown’ have been reclassified to the correct class.

Appendix III: formulas statistics

Kappa

$$Kappa = \frac{P(O) - P(E)}{1 - P(E)}$$ Equation 3

P(O) is the observed fraction of agreement and P(E) is the expected fraction of agreement and they are calculated as follows:

$$P(O) = \sum_{i=1}^{c} p_{ii}$$ Equation 4

$$P(E) = \sum_{i=1}^{c} p_{i.} * p_{.i}$$ Equation 5

Where:

p_{ii} = the proportion of cells of category i in map A and B
$p_{i.}$ = the proportion of cells of category i in map A
$p_{.i}$ = the proportion of cells of category i in map B
c = the number of land uses

Kappa*

Kappa* is almost similarly calculated as the standard Kappa statistic. However P(E) is here calculated as follows:

$$P(E)* = \sum_{i=1}^{c} p_i^S + (p_{i.} - p_i^S)*(p_{.i} - p_i^S)$$ Equation 6

Where:

p_i^S = the number of cells with land use i in subset S divided by the total amount of cells with land use i in the land use map. p_i, $p_{.i}$ and c are calculated the same way as in the standard kappa statistic (van Vliet, 2009)

$$Kappa* = \frac{P(O) - P(E)*}{1 - P(E)*}$$ Equation 7

Clumpiness index

First, the proportion of like adjacencies is calculated (G_i). The number of cell adjacencies of a certain land use class i is calculated based on the double count method (if two cells of class i are next to each other, this cell adjacency counts for two) and is divided by the total number of cell adjacencies of class i and all other classes minus the minimum number of cell adjacencies needed for a maximally clustered class i. This value G_i is thereafter corrected for the proportion of class i in the total land use map so that the clumpiness index values of all land use classes can be compared mutually.

$$G_i = \left(\frac{g_{ii}}{(\sum_{k=1}^{m} g_{ik}) - \min e_i} \right)$$ Equation 8

$$Clumpiness = \frac{G_i - P_i}{P_i}$$ Equation 9

for $G_i < P_i$ & $P_i < 0.5$ or else:

$$Clumpiness = \frac{G_i - P_i}{1 - P_i}$$ Equation 10

Where:

g_{ii} = number of like adjacencies between pixels of land use class i
g_{ik} = the number of adjacencies between pixels of land use classes i and k
min e_i = the minimum perimeter (in number of cell surfaces) of land use class i for a maximally clumped class
P_i = the proportion of the landscape occupied by land use class i.

Appendix IV: tips and remarks Metronamica and Map Comparison Kit

In this appendix we present some tips and remarks based on our experiences during the calibration process about the Metronamica model and the Map Comparison Kit. These remarks are mainly based on problems encountered while using these programs. The comments are only thoughts and therefore not verified whether it is possible to implement.

Metronamica model

The zoning maps of the Metronamica model only have only two options: 0 (not allowed) and 1 (allowed). For each function and vacant land use type, regions are chosen where certain land use types are not allowed to expand. However, in reality it is not always a manner of yes or no, but more in between options are possible. A certain land use is often allowed, but restricted in size. In natura 2000 areas, sometimes a small growth of recreational or residential purposes is allowed. In the present Metronamica zoning maps, it is not possible to model this scenario. Perhaps, we can increase the number of values in the zoning scale from two (0 and 1) to five (0, 0.25, 0.5, 0.75, 1). Also, an option is to create the possibility to enter the maximum number of cells of a certain land use type that is allowed in a certain zoned area.
Furthermore, it would be nice to have the opportunity to save a projection type in the simulated maps and the land use maps. Often, the land use and region maps are created by GIS software and in order to overlay multiple maps, a projection is needed. GIS software is developing fast and a good compatibility with GIS software will improve the user friendliness of the Metronamica model.

A major difficulty we encountered during the calibrations, especially in the case of Germany, is the modelling of new land use clusters. These clusters are mainly new industrial, residential or recreational areas and most of the times they have been built away from already existing built-up areas and main roads. Neighbourhood and accessibility settings are not sufficient for modelling these developments, because the decisions linked to these developments are mainly policy based. The randomness factor has been introduced in the Metronamica model to cover for the spontaneous human-induced actions. An increase in the randomness factor results in an increase in single pixels scattered throughout the area. However, this option will scatter around all function land use types including forest and agriculture. Moreover, mostly single cell cluster appear, because only a small chance is present that randomly allocated cells form larger clusters.
An option to improve the modelling of these new clusters is for example an expansion of the randomness factor option. In reality, single cell clusters do not appear much. Therefore, if we could be able to adjust the size of clusters that appear due to the randomness factor, we can better model this kind of developments. Furthermore, the development of these outlying clusters is not the same for every function land use type. A separate randomness factor for each function class could be an idea to solve this problem.

Map Comparison Kit

We created a map with the ‘per category comparison’ method. It would be nice to have the opportunity to show the land use map at the background of the comparison map. This land use map should be transparent in order to compare the modelled land use with its environment. Now, only the differences of two maps can be assessed, but the neighbourhood of the allocated cells is not visible. If the neighbourhood can be seen at the background, more insight is gained in the neighbourhood effects and what neighbourhood rules have to be changed. This comment is also viable for other map comparison methods.

Appendix V: attraction and repulsion graphs land use map Spain 1990-2000

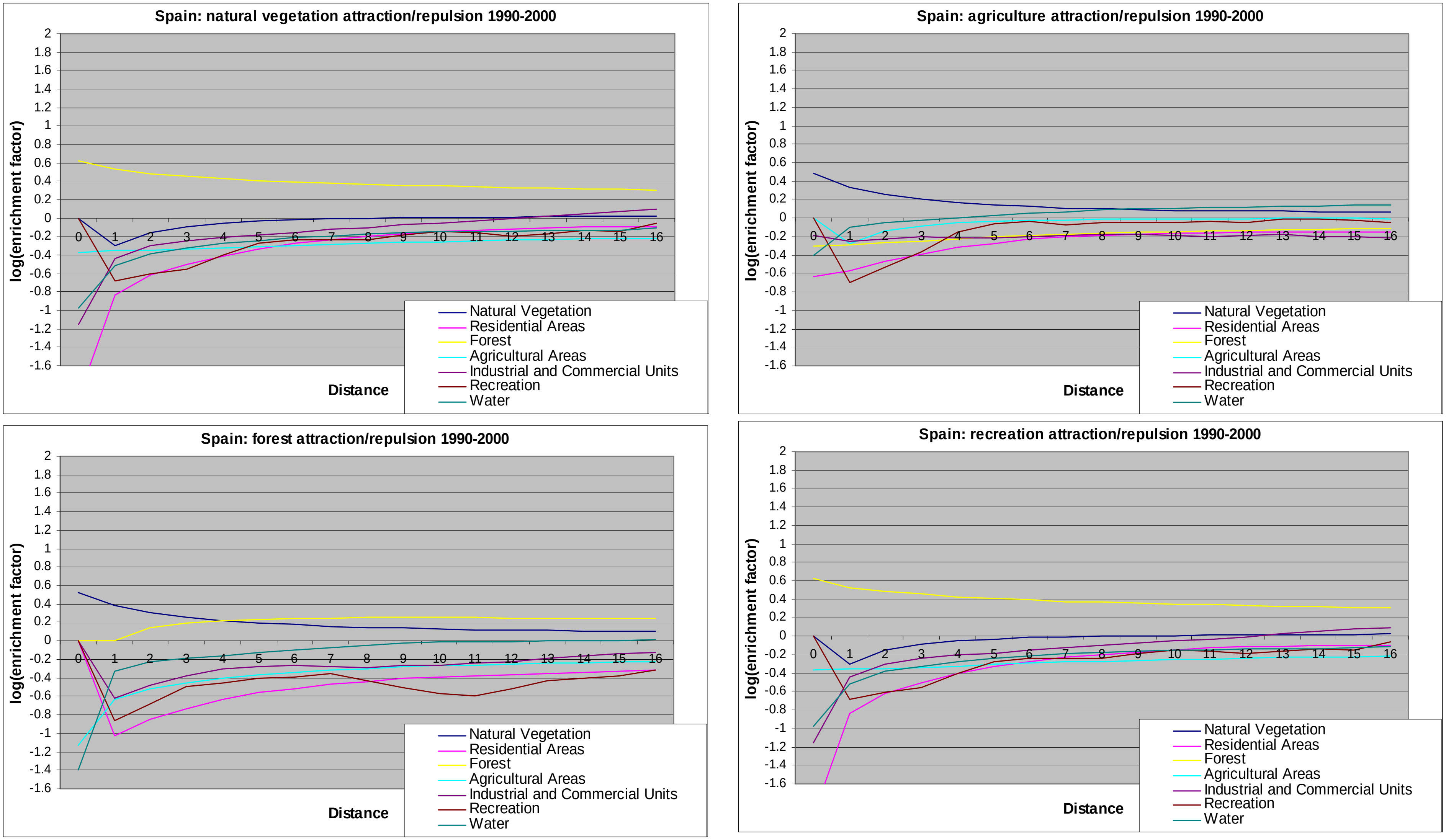


Figure 20: attraction and repulsion graphs for changed land use between 1990 and 2000 in Spain. Natural vegetation (upper left), agriculture (upper right), forest (bottom left), recreation (bottom right)

Appendix VI: attraction and repulsion graphs land use map Germany 1990-2000

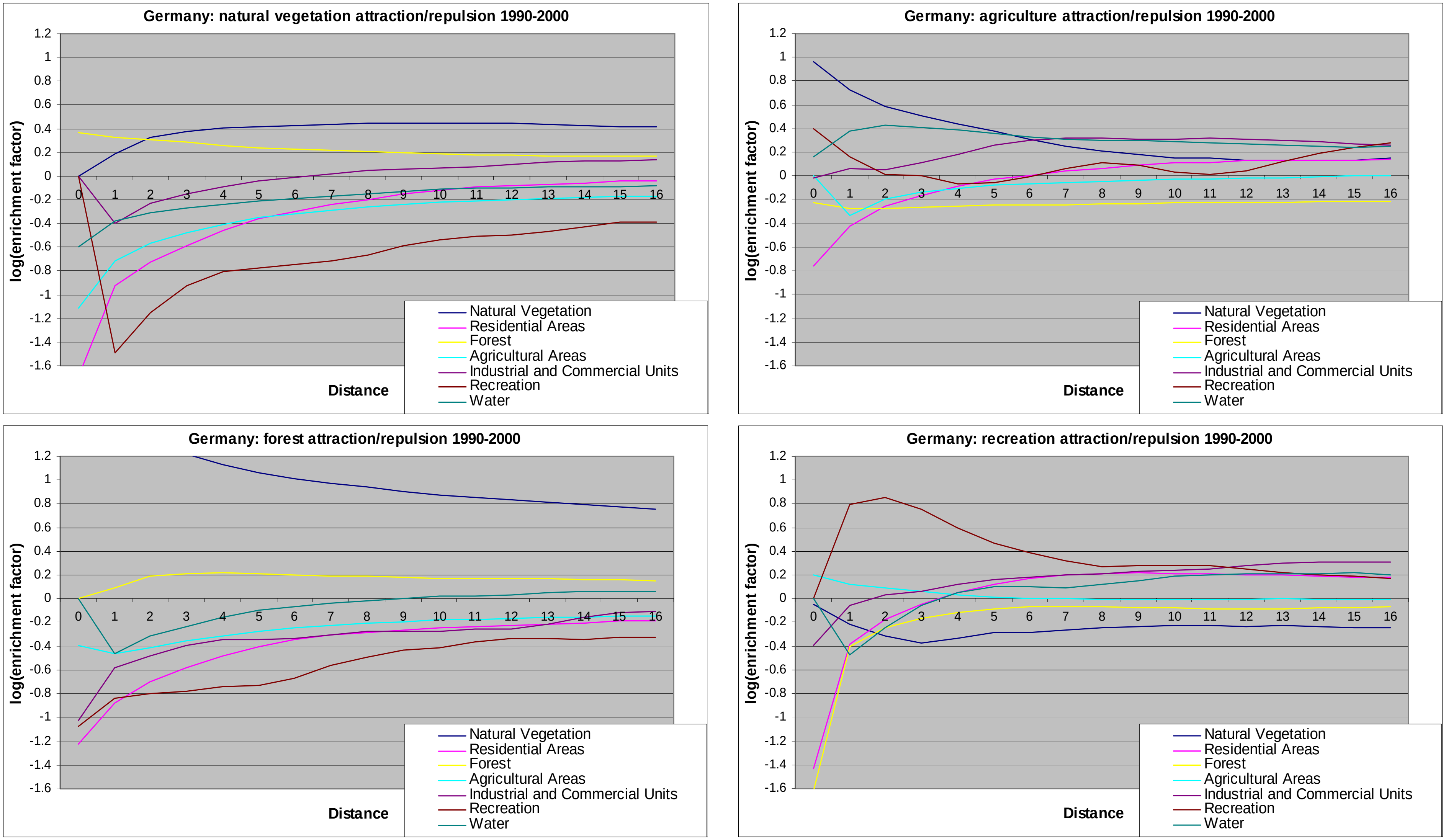
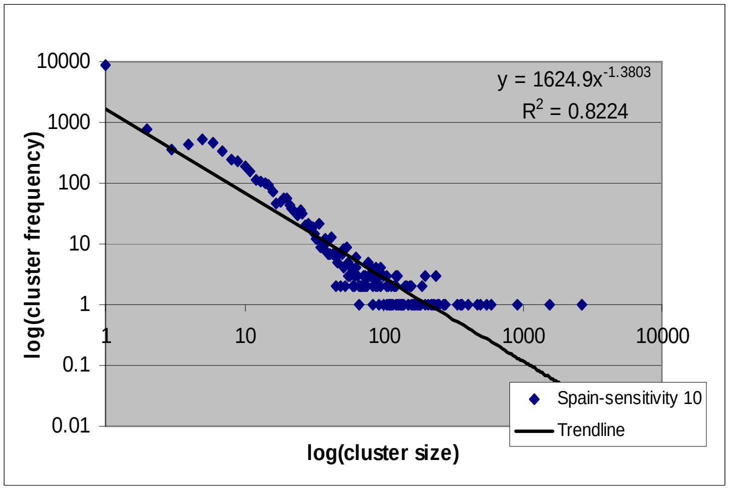
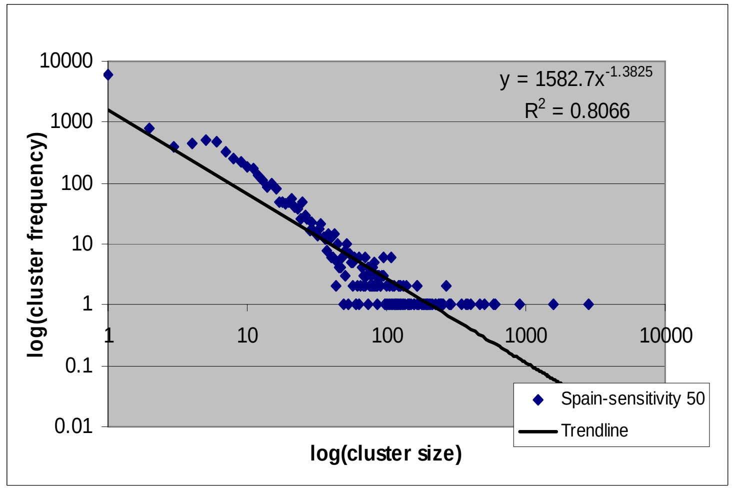
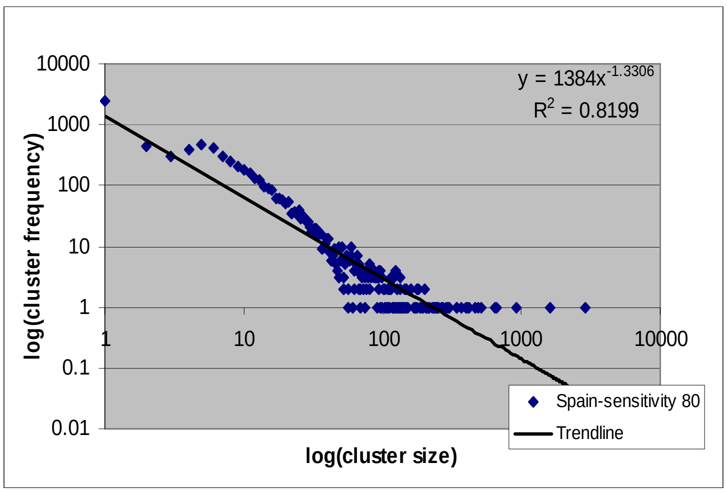


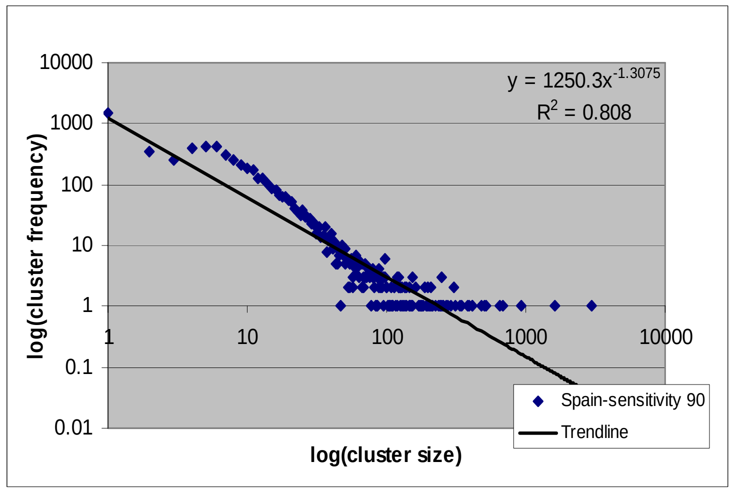
Figure 21: attraction and repulsion graphs for changed land use between 1990 and 2000 in Germany. Natural vegetation (upper left), agriculture (upper right), forest (bottom left), recreation (bottom right)

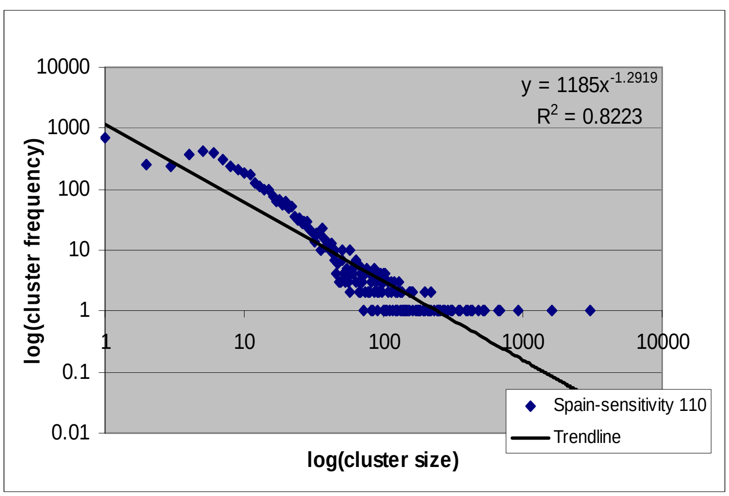
Appendix VII: cluster size frequency graphs sensitivity analyses Spain

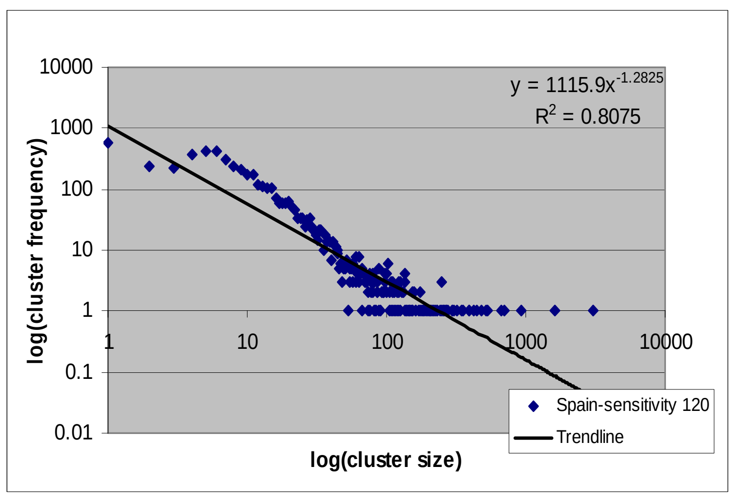












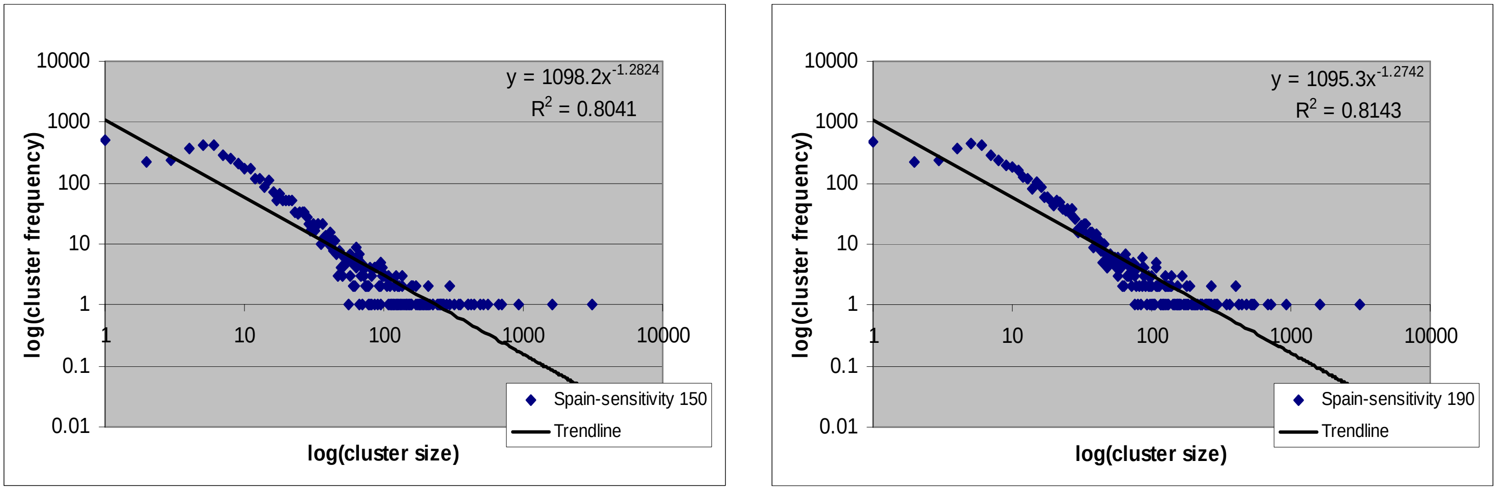
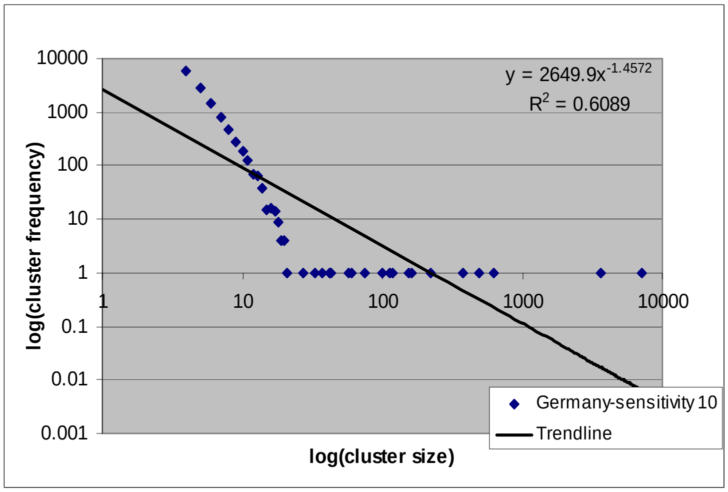
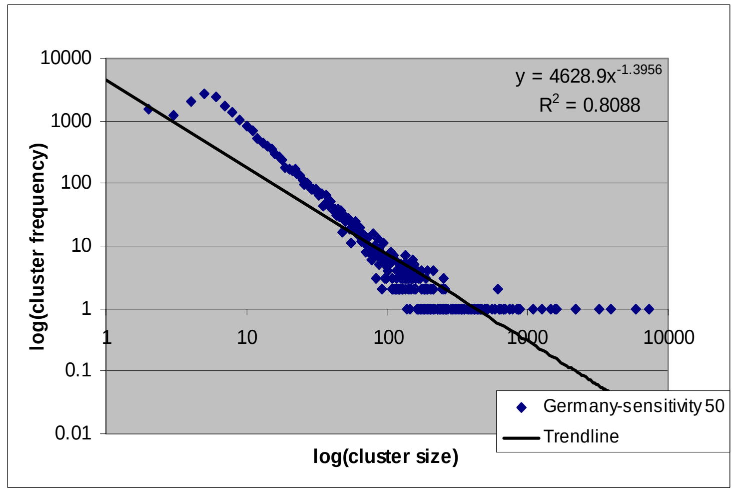
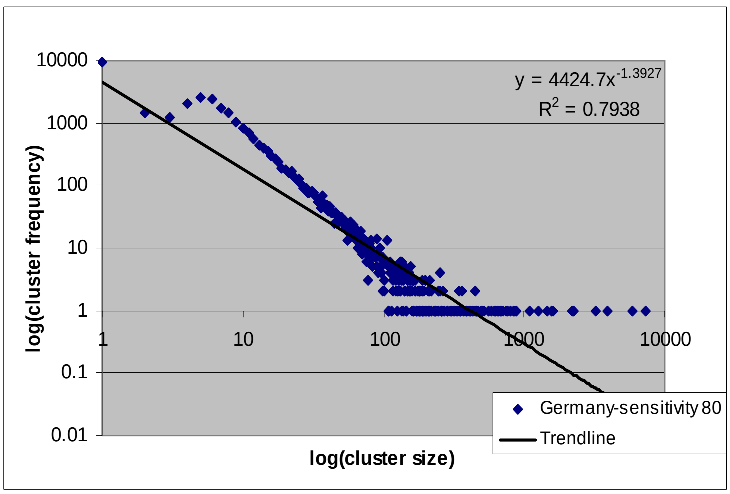


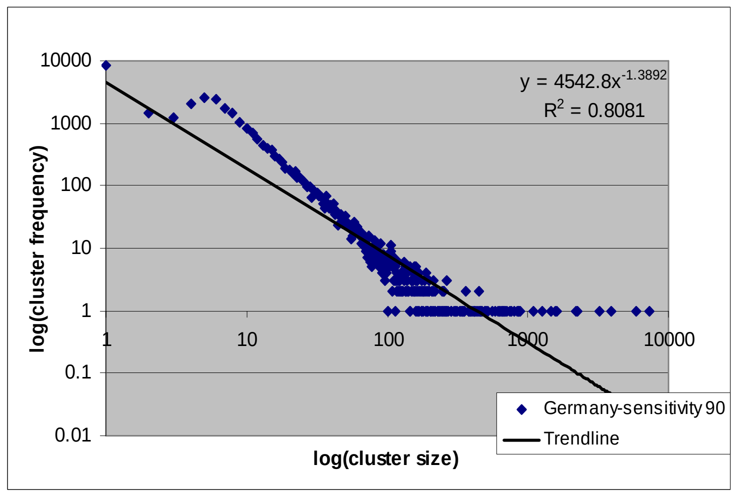
Figure 22: cluster size frequency distributions of sensitivity analysis. **Spain sensitivity analysis with values ranging from 10% of 190% of calibration two**

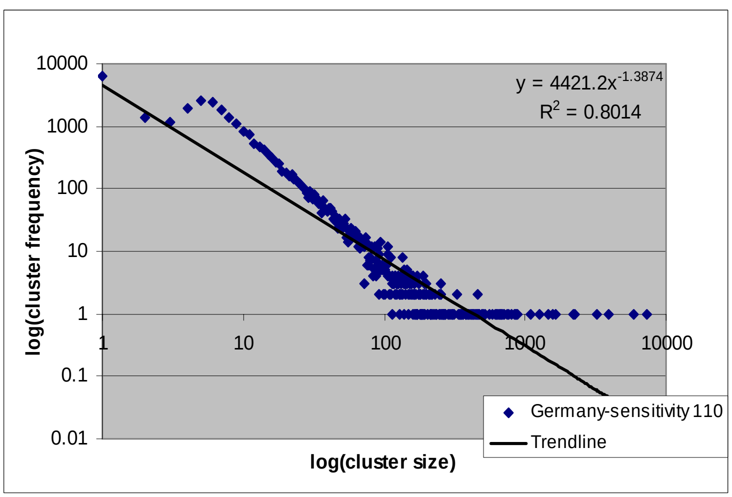
Appendix VIII: cluster size frequency graphs sensitivity analyses Germany

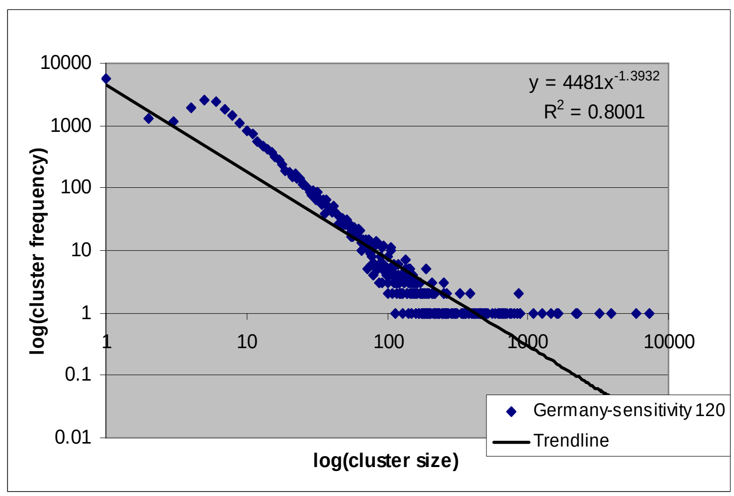


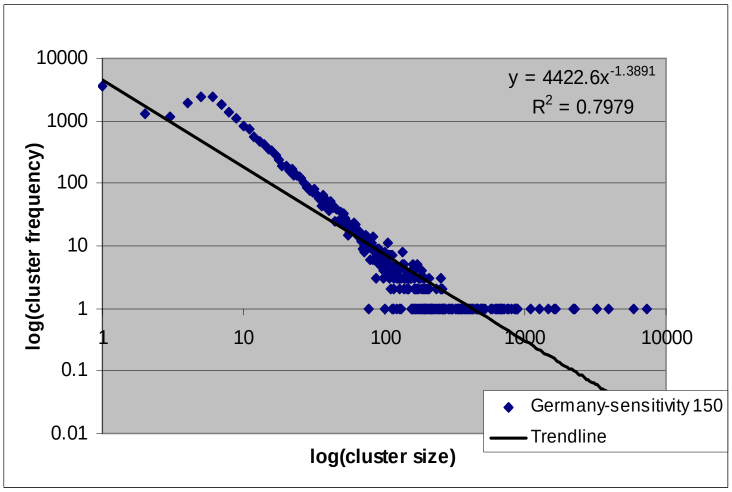












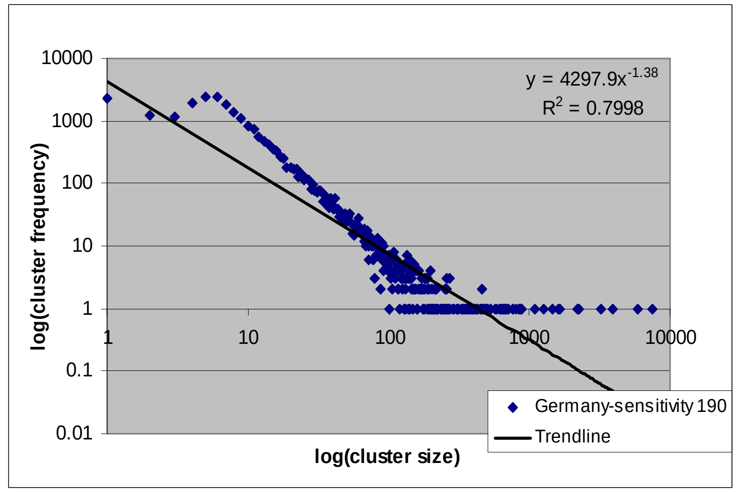


Figure 23: cluster size frequency distribution of sensitivity analysis. Germany sensitivity analysis with values ranging from 10% of 190% of calibration two