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URBAN GROWTH FORECAST USING SEGMENTED AND COMPLETE MAPS WITH THE SLEUTH SIMULATOR

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URBAN GROWTH FORECAST USING SEGMENTED AND COMPLETE MAPS WITH THE SLEUTH SIMULATOR

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URBAN GROWTH FORECAST USING SEGMENTED AND COMPLETE MAPS WITH THE SLEUTH SIMULATOR

Por

Ellen Cristina Wolf Roth

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ABSTRACT

ROTH, Ellen Cristina Wolf. **Urban growth forecast using segmented and complete maps with the SLEUTH simulator**. 2019. 99 p. Dissertation (Master Degree in Computer Science) - Federal University of Technology - Paraná. Ponta Grossa, 2019.

Commercial, industrial and public administration activities depend on projecting how cities will evolve. One of the main characteristics of a city is its internal complexity, which makes it difficult to make any planning that depends on their understanding. Computational simulation, exemplified by the growth model SLEUTH, is a possible way to help the study of this problem. Its usage, however, depends on multiple data source and several parameters that have an impact on the quality of results. The objective of this dissertation was to perform simulation studies of the city of Ponta Grossa - Brazil, using the SLEUTH model, and analyze its behavior under the use of different parameters and approaches for data input. Experiments were planned according to different partitioning of the data; simulations were performed with each of the scenarios constructed, and the outputs were compared. Till the Final calibration, it was possible to observe that the model adapts to the way the city growths, although the outputs indicated a smaller expansion than expected; but the prediction results were lower than expected. One of the regionalization schemes presented a slightly better performance, but very near to the other approaches used, not justifying the time to spend in the calibration process. The results are analyzed and possible explanations, involving the model and the data, were discussed.

Keywords: Urban simulation. Cellular automata. Cities. SLEUTH.

RESUMO

ROTH, Ellen Cristina Wolf. **Previsão de crescimento urbano usando mapas segmentados e completos com o simulador SLEUTH**. 2019. 99 f. Dissertação (Mestrado em Ciência da Computação) - Universidade Tecnológica Federal do Paraná, Ponta Grossa, 2019.

Atividades comerciais, indústrias e de administração pública dependem da projeção de como as cidades vão evoluir. Uma das principais características de uma cidade é a sua complexidade interna, o que dificulta o desenvolvimento de planos que dependem do seu entendimento. Simulação computacional, exemplificada pelo modelo de crescimento urbano SLEUTH, é uma forma possível de ajudar no estudo deste problema. Sua utilização, porém, depende de múltiplas fontes de dados e diversos parâmetros que têm impacto na qualidade dos resultados. O objetivo desta dissertação foi realizar estudos de simulação na cidade de Ponta Grossa - Brasil, usando o modelo SLEUTH, e analisar o seu comportamento utilizando diferentes parâmetros e abordagens para os dados de entrada. Experimentos foram planejados de acordo com diferentes particionamentos dos dados; simulações foram executadas com cada um dos cenários construídos, e os arquivos de saída foram comparados. Até a calibração Final, foi possível observar que o modelo se adapta a forma que a cidade cresce, porém os arquivos de saída indicam uma expansão menor do que esperado, mas os resultados de previsão foram menores do que esperado. Um dos esquemas de regionalização apresentou um desempenho levemente melhor, mas muito perto das outras abordagens, não justificando o tempo a ser gasto no processo de calibração. Os resultados foram analisados e possíveis explicações, envolvendo o modelo e os dados, foram discutidas.

Palavras-chave: Simulação urbana. Autômatos celulares. Cidades. SLEUTH.

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LIST OF ACRONYMS

ABM	Agent Based Model
CA	Cellular Automata
DLM	Deltatron Model
GIS	Geographic Information System
IBGE	Instituto Brasileiro de Geografia e Estatística / Brazilian Institute of Geography and Statistics
INPE	Instituto Nacional de Pesquisas Espaciais / National Institute for Space Research
IPLAN	Instituto de Pesquisa e Planejamento Urbano de Ponta Grossa / Ponta Grossa Institute of Research and Urban Planning
SD	System Dynamics
SLEUTH	Slope, Land use, Excluded, Urban, Transportation, Hillshade
UGM	Urban Growth Model

SUMMARY

1 INTRODUCTION

Understanding, organizing and planning cities are tasks of high complexity: there are countless processes occurring inside a city, involving factors and parameters from diverse sources as economics, demography, geological conditions or politics.

Small changes in city management may have impacts on bigger scales. A simple example is the organization of public transportation. The bus routes and stations are usually defined with respect to strategic points as streets situation, the area covered and the number of users. Modification to routes will impact users and likely alter their schedulers, but may also have an impact on the commercial development of a region, as stores and markets are attracted to places more easily accessed by population.

The location of healthcare centers, police stations and other public facilities depends on characteristics as population density, social and medical statistics. The choice of the placement of such centers will influence the decisions on public transportation and, at the same time, are affected by that system.

Commercial and industrial activities, representing the private sector, add other variables to this context. For instance, the installation of new industries may attract the development of residential areas and increase the population density of a region. This may cause movements inside of a city, with impacts on all the processes already mentioned: distribution of commerce, creation of bottlenecks in transports and other functions or, inversely, emptying of areas where investments were made by the municipality.

The context becomes even more complicated due to exogenous factors. As an example, in the city of Ponta Grossa, the arrival of enterprises as DAF, Continental and Crown were driven by global economic factors. The arrival and installation of such enterprises depends on decisions and information that can fall outside the scope of what is analyzed in the administration of a city.

As another example, Brazil major political and economic crisis in 2016 resulted in the shutting down of several businesses in Ponta Grossa; meanwhile a new private university announced its presence and in a short delay built its installations in a region where real state had relatively low cost. This will have a probable impact on the development of commerce and increase in the value of properties, which could not be predicted in view of the history of the region alone during the last decade, neither on the recession affecting the whole country.

Administrators dispose of tools, as management plans, databases, maps and routine administration software, but generally these tools present a static nature. Projections are generally based on linear regression used to draw curves of population, preview budgets and so on, with simple models that do not take into account interferences between multiple data sources. Reconstruction of lacking data is done in the same way, meaning that answers about data are based on data itself and not on the processes that generates the numbers. An example of this would be the projection of the approximate population of a city in periods where the census is not conducted.

Computational simulations may be an invaluable method in this context, helping to understand the reasons that drive certain phenomena, and, to a certain extent, to foresee scenarios and consequences of human actions and decisions, allowing early interventions and possibly higher precision.

Simulators can be effective tools for urban planning, making it possible to test different scenarios. An example is the organization of traffic signs, which, thanks to simulation, has the potential to quickly predict the behavior of a transport system and possibly mitigate problems as bottlenecks.

Of course, all the potential benefits of simulation studies do not come without costs and shortcomings. The theoretical reconstruction of a phenomenon or object, involves the modeling of variables, processes and relationships. By means of simulation, we are able to explore the model itself and the world it represents (CLARKE, 2014). This way, the study of urban systems makes it possible to better understand the consequences of individual level choices at a global level. As this is one of the main objectives in system studies, simulation creates the possibility of finding links between the macro and the micro scales (BENENSON; TORRENS, 2004).

In many natural systems, having a mechanical understanding of how a certain phenomena work and representing this knowledge with mathematical equations and models, is enough to simulate its behavior with precision. But in urban systems, this is not enough, as it involves human behavior and a bit of randomness (ALLEN, 2012). Cities are complex emergent systems; they are adaptive and dynamic, with complicated relations between microscopic and macroscopic behavior. Dividing this kind of system into smaller and simpler modules helps to understand and observe the interactions of the entities (HOEKSTRA; KROC; SLOOT, 2010; BENENSON; TORRENS, 2004).

The study of cities has resulted in a certain number of modeling and simulation techniques, especially in the field of urban growth and land use. As urban systems are very complex and their attributes are often influenced by different characteristics within the system, it is important to note that sometimes models can have different results than reality. Models are simplified forms of reality and their characteristics may not be able to fully simulate the reality being studied.

Cellular Automata (CA) are mathematical models, based in a grid of cells which evolves in discrete time and states, using rules (DOWNEY, 2018; WOLFRAM, 1983). CA models are used in several areas of science, including anthropological, historical, physical and biological contexts. They have a relatively simple construction that contrasts with the complexity of the systems that are studied with their help. They were already used in varied kinds of simulations as biological modeling (ERMENTROUT, 1993), chemical reactions (SCALISE; SCHULMAN, 2016), microstructure evolution (QIAN; GUO, 2004), epidemics spread (WHITE; DEL REY; SÁNCHEZ, 2007) and are frequently employed in the study of cities.

In urban simulation it is common to observe models that associate CA and Geographic Information Systems (GIS). Similar aspects may be found in both, the approaches are based in simple spatial interaction, and grid/cells representation can be related with raster-based (WAGNER, 1997). CA landscape input data may be drawn using GIS and the model output also may be represented using it (CLARKE; HOPPEN; GAYDOS, 1997; BATTY; XIE; SUN, 1999; LI; YEH, 2000). The use of both together overcome some limitations they have, while CA models handle with temporal dimension and spatial models, the GIS may help to define transition rules. (WHITE; ENGELEN 1997; PARK; WAGNER; 1997; LI; YEH, 2002)

In Brazil, there is an extensive terrain to be developed, but this implicates in human commitment, exploration of the available studies, development of new models and tools, integration of systems and data gathering, and the change of a paradigm.

1.1 OBJECTIVES

This project develops a simulation study of Ponta Grossa, employing a widely used tool called SLEUTH. Given the intrinsic difficulties surrounding model calibration and the validation of results, the central objective of the study is to compare two modeling approaches: a global simulation where the entire city is processed by the software, followed by a regionalization of the map with the separate simulation of each parcel. The hypothesis of the study is that the segmented approach can obtain a better calibration; consequently, forecasts would be more accurate.

The main objective of the study is the comparison between modeling approaches: global or segmented. This involves the following goals:

- preparation of all input, which may imply reconstruction or interpolation for non-available data (Figure 1);
- carrying out the simulations, compiling and tabulating data;
- performing quantitative and qualitative analysis of results.

Figure 1 - Example of the construction of an urban spot using satellite maps overlaped

Source: adapted from Google Earth and INPE

A few initial obstacles have been identified. One of the main ingredients for simulation and modeling - information in digital form - is not systematically collected and stored by public administration. Some data sources have been identified in the beginning of the work and are expected to satisfy the needs. One possible remedy to the problem is to make use of interpolations. A second concern is model calibration, in view of a possible lack of data: the less data available, the more sensible the simulation will be to parameters. The regionalization of the city map is expected to ameliorate the results.

1.2 ORGANIZATION

In the next chapter the Urban Simulation problem will be discussed, followed by a section on the Cellular Automata model. After this, in Chapter 4, Cellular Automata in Urban Simulation and the SLEUTH model will be described. The development of the study is found in Chapter 5 and, finally, chapter 6 presents results and conclusions.

2 URBAN SIMULATION

Deep changes are happening in geographical distribution and the size of the world population. The lack of urban planning is felt, as some places still lack of basic resources as sewage and piped water, and the traffic disorder is present in several places. The actions taken on a city have direct and indirect impacts on different aspects, from traffic organization to citizen’s security. Urban processes should be monitored and planned, aiming the sustainable development of the cities and the clever use of the available resources (SOUZA, 2002; DEEP; SAKLANI, 2014; TORRENS; O'SULLIVAN, 2000; KOURTIT; NIJKAMP, 2013; TEZA; BAPTISTA, 2005; BASTOS, 2007).

Cities can be compared with living systems, composed of different sub-systems, which are full of connections and complex interactions. Micro and macro interactions can shape city patterns and its evolution, and the system space and time are dynamics. The city is a complex system, and a first step to understand it is to study its subdivisions separately. Among these subdivisions, it can be cited the traffic sub system, urban growth, and land use (CROOKS, 2006; MEIER, 1962).

One of the most important things to understand about a city is how it grows. This process has an important role in public administration; as an example, this information helps project the needs of new public resources, like transportation or healthcare centers, and project the extension of basic services as water and electricity supply. Predictions about urban growth are also crucial in the private sector, providing background for study of feasibility of new business establishments. Finally, it may help to understand changes in the social organization of a community (PARK; BURGESS, 2012; BARROS, 2004).

The way a city grows is not a universal process; although there are similar aspects in all cities, the exact evolution of each one follows different patterns (MA; HANTEN, 1981; CHENG, 2003; BASTOS, 2007; ROCHA, 2012). Social aspects also influence the evolution of a city in several ways; municipal elections are a simple, yet significative example (HAASE et al., 2012). Natural factors, such as possible flooding, and the transformations that happened through time also have impacts (POLIDORI, 2005). Briefly, urban transitions are a result of physic, socioeconomic and environmental aspects that compose a complex system, full of different spatial and temporal behaviors (CHENG, 2003; BOURNE, 1982; ROCHA, 2012). It is possible to use the same model for the different cities because the historical data of each of them show their development patterns and transitions, defining how the model will behave (SANTÉ et al., 2010).

An urban system is formed by two different "worlds" (SIEBERT, 1999): the formal city and the not formal. The first correspond to the fraction that respects policies, gives origin to official data, pay taxes and remain within the laws imposed by the government. The second is the city where land is invaded, taxes are not paid and statistics and data are wrong or not available. These two different worlds have influence on the system development.

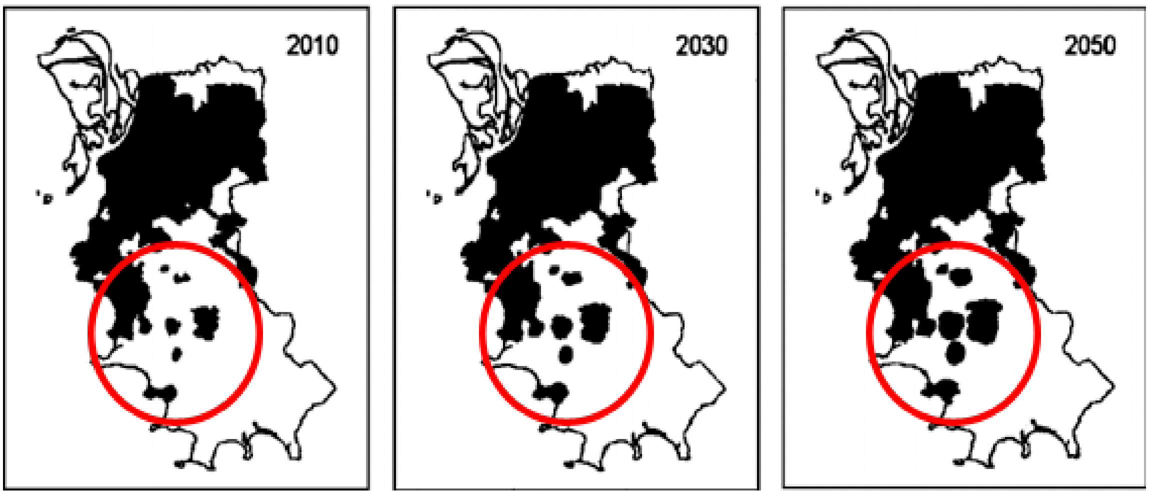
All these characteristics make necessary for administrators, economists, and investors to have tools to help them understand the dynamics of a city and make decisions.

Urban models are tools applicable in many tasks related to city planning. They may indicate environmental and social problems before they actually happen (FORMAN, 2008). City Traffic (SIMON; NAGEL, 1998), crime patterns (LIANG, 2001), evolution of land use patterns (WHITE; ENGELEN, 1993) and city growth (AL-SHALABI et al., 2013). The analysis of model predictions brings the possibility of applying early intervention policies and adaptations, to mitigate negative effects, also may raise governmental and public awareness about social and physical aspects, and helps to address possible complications (BAYNES, 2009; FORMAN, 2008; PETROV; LAVALLE; KASANKO, 2009).

The acceleration of the urban growth makes the study of this aspect one of the most important to be understood. Due this phenomenon in the recent history, planning and managing is becoming more complex. The expansion makes pressure on land resources, bringing environmental and social problems, which makes this kind of simulation significant (LIU et al., 2014; LEAO; BISHOP; EVANS, 2004; HEROLD; GOLDSTEIN; CLARKE, 2003).

The most typical form of this kind of study represents land use changes along of a period of time. Figure 2 shows one example, with the land use model UGM (Urban Growth Model) applied in the city of Porto Alegre, Brazil. UGM is the principal module of the software SLEUTH, used in this project; the land-use changes are categorized by the transformation of not-urban areas, as farms or woods, represented by the color white, in roads, buildings, and others urban forms, represented in black (CHENG, 2003; LEAO; BISHOP; EVANS, 2004).

Figure 2 - UGM simulation of the urban growth of Porto Alegre - 2010 - 2050



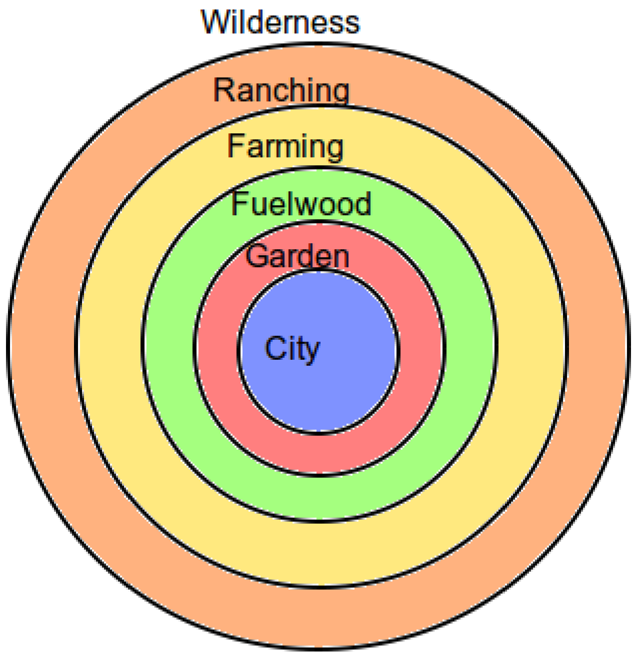
Adapted from: Leao, Bishop and Evans (2004).

Given the large scope of the problem, a number of techniques have been developed for the study of cities. It is worth to draw a historical perspective of how simulation evolved; this will be briefly discussed in the next section.

2.1 THE HISTORY OF URBAN SIMULATION

Possibly the first known model for city studies was developed by the German economist von Thünen, in 1826. It was a descriptive model for a region (as a fief) comprising an urbanized nucleus surrounded by farmlands. The model was a base for others approaches, as Hoover (1936) and Dunn (1954). The von Thünen model (Figure 3) considered three factors: the distance from the market, the goods price and the land rent. It was based on the hypothesis that the transportation cost and distance were inversely proportional to the land-use intensity (HENSHALL, 1970).

Figure 3 - The von Thünen model



Source: adapted from Grotewold (1959).

In 1909, Weber created the Industrial Location Model, extending von Thünen's model to address the problem of urban growth. Following the work of Weber other studies were developed, as the Central Place Theory, by Christaller (1933) and Multiple Nuclei Model from Harris and Ullman's (1945), but they did not take urban development into account to the same extent (LIU, 2008).

Urban models were intensively used in the quantitative revolution[1], in 1950s, and lasted till the late 1960s (BATTY, 1981). The major development of urban models was in North America, caused by the spread of the car owners (BATTY, 1976). The models were focused in operational decisions, as highway impacts and urban problems (PUTMAN, 2013; WADDEL; ULFARSSON, 2004). The models were used in transportation studies, to plan the needs and accommodate the demand, using as a base the people movement and the effects of the land use (FOOT, 2017).

The development of computers made it possible to work with complex mathematical models and a set of styles, techniques and applications, dealing with problems as land use, transportation, population and urban economics. They were

[1] The Anglo-American geography transformation, in the 1950s and 1960s, when new ways of research were introduced in the area, as inferential statistical techniques, abstract models and new theories (GREGORY et al., 2011).

initially built using techniques as linear analysis and mathematical programming (KILBRIDGE; O'BLOCK; TEPLITZ, 1969).

These studies were focused in modeling techniques, and researchers started to use mathematical tools to make qualitative analysis. This pattern last till the late 1980's, when the studies about complex systems gained attention and new ways to study cities were devised. In this period progresses also occurred in nonlinear systems and Chaos Theory. GIS (Geographical Information System) were developed, and made it possible to use improved data and new techniques for data analysis (ALLEN, 1997; WEGENER, 1994; LIU, 2008).

All the available tools, data and mathematical techniques lead to different simulation studies. It is important to identify, how each element, in this set of tools, can be useful to build a model. This will be examined in the next section.

2.2 IMPORTANT FACTORS FOR URBAN SIMULATION

Urban dynamics are composed of multiple processes and, as such, it can be influenced by many different events and parameters. The expansion of a city is one of these processes and depends on things as population growth, roads under construction, economy situation and infrastructure (SUDHIRA, 2004). One method to analyze this context is by identifying forces as repulsion and attraction that influence the urban growth and the definition of the land-use (DENDRINOS, 2002). An example of this are regions with higher costs per area act as points of repulsion to the occupation by productive sectors (manufacture, industry), who prefer to have installations in regions as suburbs that can maximize the return on investments. Residential and commercial areas are also related, and function as a probabilities system, increasing and decreasing the potential of the locations (KRAFTA, 1999).

The space distribution and classification of areas according to the usage is one of the first factors affecting urban dynamics (SPINELLI; KRAFTA, 1998). Residential areas are usually created in the vicinity of other residential areas, giving the possibility of extending the infrastructure already existent. Commercial activities and the availability of access routes are other factors that function as attractors. Proximity to industrial areas, on the other hand, generally represent an inhibitor for the construction of residences, although this situation can be balanced by the attractive advantages already listed (ALMEIDA, 2003; BARREDO, 2003). As it happens with residential areas, industrial areas growth is impacted by the road accessibility and the proximity to other areas with the same type of occupation (BASTOS, 2007). Growth saturation at the center of the cities may cause a shift of activity to peripheral areas (SAURIM, 2005), something known as ‘decentering’ (BURGA, 2009).

The existence of parks, rivers, airports, roads and transportation may affect the future occupation of areas; “dead” spaces, which cannot be urbanized, soil particularities and regulations regarding allowed activities can have influence over the transitions (WHITE; ENGELEN, 1997; PEDROSA, 2003; GRANERO; POLIDORI, 2002; SAURIM, 2005). Social factors, as development politics, may be considered in some models too (BASTOS, 2007).

Macroscopic properties, as the placement of residential areas or the distribution of population, may have a strong dependency on microscopic structures of a city, as the network of local commerce, employment opportunities. Each level of the system can have been affected by what happens at the lower scale structure. This reveals that the different system levels are local and global phenomena at the same time, the system as a hole is dependent of the individual's actions, and the global is not predominant over the local neither the local over the global (ROCHA, 2012). This relation between the micro and the macro scale can enter models of land-use dynamics, which may show as the decisions on both scales work together. (LAUF et al., 2012).

Small modification in the initial data may be amplified over time making system predictions harder, a phenomenon popularly known as butterfly effect. As an example, a single investor that opens a new business may encourage similar initiatives that, over time, may change the characteristics of a neighborhood. By observing how small modifications on initial conditions can lead to big changes in the system future, it is possible to understand future possibilities, explore the influence of the variables in the process, and create strategies to administer the urban growth (ROCHA, 2012).

Another relevant modeling aspect is the fact that processes occurring simultaneously in a city may have different time scales. For instance, traffic conditions depend on the hour and day of the week, while cycles as increase or decline of population, changes in buildings construction and development of neighborhoods may take years to have significant changes (ROCHA, 2012). Integrating processes that operate in very different temporal and spatial scales occurs in many branches of science and is a problem on its own (HOEKSTRA et al., 2010). Most simulators, to our knowledge, model cities using processes that occur at the scale of years. The diversity of parameters, rules, data sources, and non deterministic aspects compose a challenging task. The expansion of urban areas is, on first sight, a chaotic process, encompassing several types of events and phenomena happening simultaneously. However, a more detailed examination may reveal the presence of patterns in the system, simplifying its understanding (SAURIM, 2005). This point in the direction that the difficulties can be mitigated by breaking the system down into modules or elements (POLIDORI, 2005).

As it can be seen the study of cities is a rich field of investigation, what has resulted in many modeling approaches. They include mathematical representations, techniques to incorporate human behavior and techniques as fractals that were born from the field of complexity. The next section overviews some of the possibilities.

2.3 MODELING APPROACHES

Digital maps, although being crucial, are only the initial information required to model a city; it is also necessary to find representations for the forces and dynamic processes that arise in the system (BATTY; STEADMAN; XIE, 2006). There is a variety of techniques to urban simulation models, ranging from the traditional models, like mockups, to mathematical-based representations. They can be classified according to attributes as the degree of simplification, and construction style.

The simplest category is Scale models, consisting of miniatures or mockups with some transformations. An intermediate level is occupied by Conceptual models, focused in components and their relationships; they can be expressed in diagrams and verbal language. Lastly, the more complex category contains various types of Mathematical models. Which have subclasses, depending on its characterization; they could be descriptive, static, dynamic, stochastic, among others (THOMAS; HUGGET, 1980; LIU, 2008). The following section will make an overview of three modeling techniques that are frequently found in the literature about urban simulation.

2.3.1 System Dynamics

System Dynamics (SD) models allow the partition of a simulation into three subsystems: business, housing and population, and also allows the inclusion of socio-economic aspects (SANDERS; SANDERS, 2004). Basically SD models are composed by stocks and flows. They can represent interdependencies and interactions of local systems. Models can have nonlinear responses, irreversible changes and long lag times (THEOBALD; GROSS, 1994). They have the ability to work with large sets of temporal data and include explicit feedback loops in the simulation (HAASE et al., 2012; STERMAN, 2000).

SD models are not spatially explicit; in other words, these models do not consider a map of a city and can not calculate results related to locations. Instead, their behavior is described by differential equations and functional relationships that have a more global character and that can change during the simulation. SD can use “what-if scenarios” and predict changes in complex systems, being an option to support recommendation and examination of policy decisions (HAASE et al., 2009).

This kind of model is able to simulate social-demographic changes and also urban shrinkage (HAASE et al., 2012). Reported applications include landscape change simulation (DHAWAN, 2005; STERMAN, 2002) and land-use changes (LI; LIU, 2007). However, it cannot handle spatial variables, which can influence the land-use change, and also is not capable of revealing spatial pattern changes (HAASE et al., 2012).

Other examples where SD models have been used include:

- Forrester (1970): a general model was constructed by connecting subsystems "business”, "housing" and "population". This model could simulate situations as rapid population growth;
- Haghani, Lee and Byun (2003): transportation and land-use were combined with the objective of estimating scenarios; transport policies were used as a base tool;
- Eskinasi and Rouwette (2004): a SD model aimed in analyzing the impact of future policy interventions impacts on the social housing market.

2.3.2 Agent-Based Models

The word “agent” has countless definitions in the literature and trying to obtain a consensus is out of the scope of this study. The relevant aspect to consider here is, agent based models (ABM) refer to the idea of representing individual decisions and actions that may be relevant in a given urban simulator (EPSTEIN, 1999).

Models in this category are usually spatially explicit, with maps describing the land characteristics (DUNNING et al., 1995), and may include autonomous decision-making individuals. Each individual can have different properties and strategies (BONABEAU, 2002; SAWYER, 2003; PARKER et al., 2003), what can be valid, for example, to study micro-scale phenomena in transport systems (HAASE et al., 2009).

Another example where modeling the perspective of individuals is a reasonable approach, is to simulate social processes, as the development of a residential area by an artificial society (LI; LIU, 2007; LIGTENBERG; BREGT; VAN LAMMEREN, 2001; HAASE et al., 2009; LE; SEIDL; SCHOLZ, 2012).

Some general examples of the application of these ideas are (HAASE et al., 2009):

- ILUMASS, by Strauch et al. (2005): a model focused on urban traffic, that also includes activity behaviors, land use changes and effects on the environment;
- Ettema et al. (2007): a model built to predict urbanization using behavioral agent;
- Miller et al. (2004): the model simulates evolution of a region focused on transportation;
- Wadell et al. (2003): the tool UrbanSim analyzes the impact of distinct planning strategies, linking transport and land use.

2.3.3 Cellular Automata

Cellular Automata (CA) is a modeling technique with a broad spectrum of application, ranging from fluid dynamics to social sciences. One of main characteristic of this model is the use of a grid of cells, representing the global behavior of the system that emerges from local rules (COUCLELIS, 1985; FANG et al., 2005).

The execution of CA models can lead to complex patterns that result from the application of simple individual rules (ROCHA, 2012), a concept viewed as very amenable to urban simulation (CLARKE; GAYDOS, 1998; BATTY, 1997).

CA is probably the most widely adopted technique in the field of urban simulation, being simple to understand and to use, and at the same time, flexible enough to accommodate complexity without compromising the understandability of the model itself. This technique was chosen in this work and will be detailed in the next chapter.

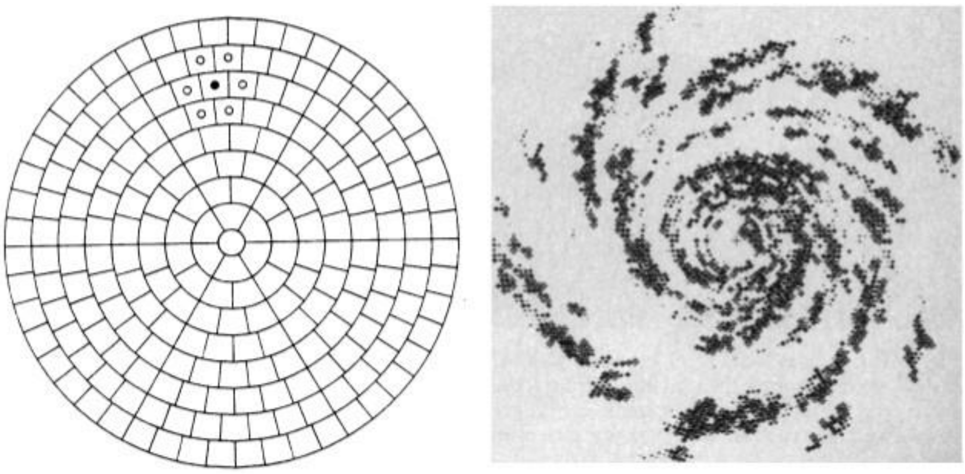
3 CELLULAR AUTOMATA

Cellular automata (CA) are simple and dynamic models of physical systems, with discrete time and generally discrete states. A model based on CA divides space into discrete units (cells), which are governed by rules that define how the system must evolve. Although having a simple structure, a CA model is capable of generating complex patterns in the system's evolution (DOWNEY, 2018; WOLFRAM, 1983).

CA models have some properties in common. They are composed of a matrix or grid of cells that evolves in discrete steps of time; each cell has a state among a finite set of possibilities; cell evolution is dependent of the state of neighbor cells; and the neighborhood relation is uniform and local (WEIMAR, 1997).

Figure 4 shows an example where a CA model is used to represent the structure of a galaxy, based on a percolation process (SCHULMAN; SEIDEN, 1986; SCHIFF, 2011). This study is a sound example of how a CA model can be used to capture the most significant aspects of a phenomenon and replicate the general properties and behavior of a system.

Figure 4 - Simulation of a Spiral Galaxy using the CA Model



Source: Schulman and Seiden (1986).

CA models have been given different names, such as "cell structures", "mosaic automata", "homogeneous structures" and "interactive arrangements". (SANTÉ et al., 2010). One of the principles of CA is that the local transition function determines the current state of individual cells based on what occurred in the previous step. Since rules are local, each cell works as an information processing unit. The neighborhood is usually defined as the immediate adjacent cells. As a consequence, in such organization a cell always influences the behavior of the others in the evolution of the system and the result of each interaction has an impact on the next steps of the model (VIANA et al., 2014).

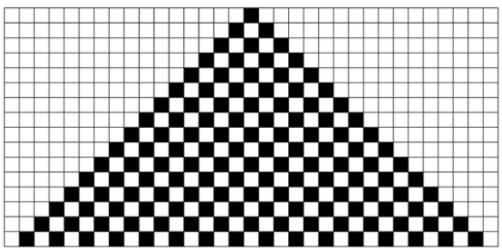
Complex systems can be defined by properties as emergence, self-organization and nonlinear dynamic behavior (SCHALDACH et al., 2011; BERLING-WOLFF; JIANGUO, 2004; BARREDO et al., 2003; RAVETZ, 2000). These aspects can be perceived in the CA models by the following characteristics: creation of complex patterns, that indicate non-linearity; interaction in micro scale reflection on the global system, showing self organization; and the impossibility to define the future model states, just observing the past ones, revealing the model emergence (VIANA et al., 2014; ROCHA; MORGADO, 2007).

Cells can be grouped in different ways and be controlled by different rules; in an extreme case, each cell can have its own set of rules. In addition to these characteristics, the spatial representation of entities and relationships between cells allows to create different types of grids and different configurations to be used for system modeling (ROCHA, 2012). Most CA models follow these fundamental characteristics (SCHIFF, 2011):

- uniformity: the cells update follow the same rules;
- synchronism: the update of all cells happen at the same time;
- locality: the rules are local.

Classic CA models are organized as one-dimensional, which can be visualized in Figure 5, that represents the evolution of a one dimensional automaton where the cells change according to the colors of its neighbors; or bi-dimensional.

Figure 5 - Vertical sequence of states of a one-dimensional Cellular Automata

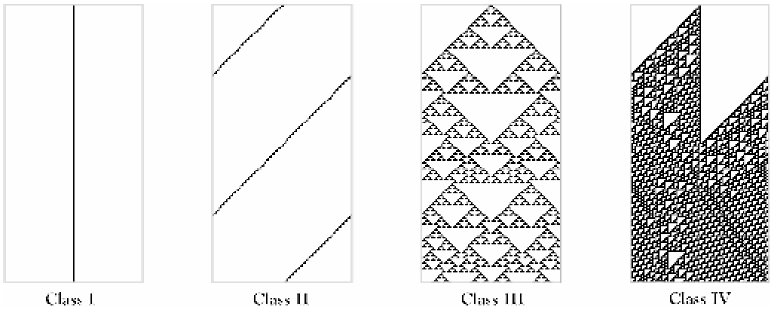


Source: Wolfram (2002).

Simulations based on CA models can show behaviors varying from very simple to very complex. A classification of automata based on those behaviors was proposed by Wolfram (1983), and has four categories or classes (Figure 6) (ILACHINSKI, 2001; DOWNEY, 2018; FERREIRA, 2009):

- Class I: deterministic; after a finite number of steps, evolve to a homogeneous and stable state;
- Class II: slightly random; initial patterns evolve into stable and oscillating structures. The pattern contains structures of its own in miniature;
- Class III: exhibit pseudo randomness; evolves into chaotic states. Models in this class have great dependency on initial conditions, and small variations can lead to strong instability;
- Class IV: can be considered Turing Complete; evolves into structures that interact in complex ways and create local patterns that can survive for long periods of time.

Figure 6 - Wolfram Classes



Source: Avnet (2000).

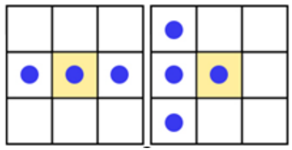
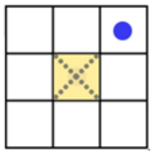
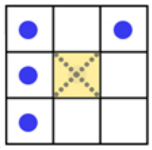
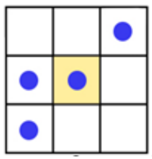
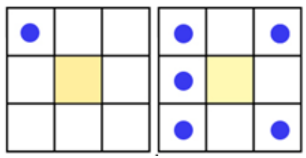
AC models may be deterministic, when their behavior can be represented by a finite state machine; and probabilistic, when transition rules are associated with probabilities (SIMÕES, 2016).

3.1 CELLULAR AUTOMATA HISTORY

The most accepted origin of Cellular Automata is the combination of the works of John von Neumann and Stanislaw Ulam in 1942. John von Neumann was working on a model of self-reproducing organisms. Stanislaw Ulam, who studied crystal growth (PICKOVER, 2009), simplified the von Neumann model into a 2-dimensional cellular automata. Von Neumann believed that a complex model was needed to represent varied behaviors, so he used a large number of cells, each of them could have 29 colors and complicated transition rules (WOLFRAM, 2002).

CA models became popular with the introduction of Conway's Game of Life, in 1970; this two-dimensional model simulated a colony of simple organisms. Each cell had two states, 1 - alive and 0 - dead; the transition rules depended on the 8 neighbor cells as represented in Chart 1. In Chart 1, the target cell, which is being updated, is represented by the yellow cell; the living cells by the blue dots; and the dead cell by the x symbol (FERREIRA, 2009; SCHIFF, 2011):

Chart 1 - Game of Life Rules

Rule	Matrix configuration
a living cell, remains alive if it has two or three living neighbors	
a living cell, dies of loneliness, if it does have just one living neighbor	
a living cell, dies of overpopulation if it has more than three living neighbors	
a dead cell, becomes alive if it has exactly three neighbors	
if none of the previous cases occurs, the cell remains dead	

Source: adapted from Benenson and Torrens (2004).

The execution of the game caught attention of researchers. Certain cell group's exhibit periodic behavior and are known as "blinkers". Other groups seem to travel through the matrix and are known as "gliders". It is also possible to observe that, regardless of the initial configuration, there are three possible states that the system can achieve (FERREIRA, 2009):

- extinction: all model cells die;
- stability: the model reaches an unchanging state;
- oscillation: the model cycles through a sequence of two or more states.

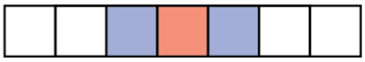
3.2 NEIGHBORHOOD

The neighborhood is one of the fundamental characteristic of any CA model. It corresponds to a set of cells, chosen according to spatial and temporal criteria, which will be taken as input by the transition rules of a given cell (HADELER; MÜLLER, 2017; COLOMBO, 2011; DEUTSCH; DORMANN, 2005; ZHAO; BILLINGS, 2006; PINTO; ANTUNES, 2007).

The cell that’s going to be updated may or may not be part of its own neighborhood. The neighborhood can include cells that do not have direct contact with the one being analyzed. It is possible to weight the influence of neighbors according to their distance. The neighborhood can be asymmetric (DAHAL; CHOW 2015), although symmetric ones are the most usual (CARTWRIGHT, 2008; MAEDA; SAKAMA, 2007).

In one-dimensional models the cell grid is frequently considered as infinite; in this case the neighborhood is usually composed by left and right cells. This kind of neighborhood is known as Radial (Figure 7).

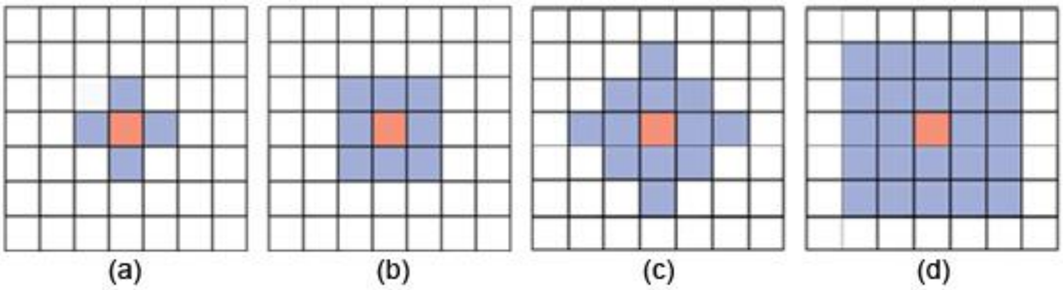
Figure 7 - Radial Neighborhood



Source: adapted from Maeda and Sakama (2007).

Two dimensional grids are the most usual, and have some neighborhood configurations that are known by particular names. The most used 2-dimensional neighborhoods are the Von Neumann (Figure 8a) and Moore (Figure 8b), containing cells that have direct contact with the cell being updated. As more cells are added it results the r-Radial, or Von Neumann extended (Figure 8c), and r-Axial, or extended Moore (Figure 8d) (DEUTSCH; DORMANN, 2005).

Figure 8 - (a) Von Neumann's neighborhood; (b) Moore's neighborhood; (c) r-Radial Neighborhood; (d) r-Axial Neighborhood



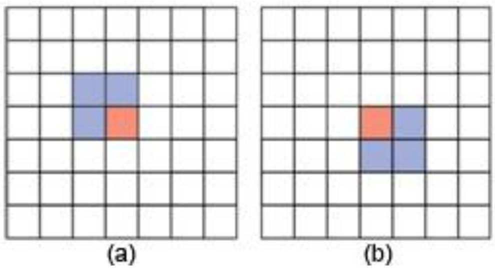
Source: Adapted from Maeda and Sakama (2007), Deutsch and Dormann (2007).

A quite different neighborhood is the so-called Morgolus, which have the following characteristics (SPEZZANO; TALIA, 1999; COLOMBO, 2011):

- Finite and uniform set of cells, forming a 2x2 block;
- Transition rules are applied to the blocks, not to the individual cells;
- No information is exchanged between adjacent cells;
- Two types of neighborhood configuration are used; they alternate between even and odd steps.

These characteristics can be visualized in Figure 9, where the blue cells are the neighbors of the red cell. The set of cells forms a block, which behaves in the even step as Figure 9a, and in the odd step as Figure 9b.

Figure 9 - Neighborhood of Margolus (a) Even - (b) Odd.



Source: adapted from Colombo (2011).

3.3 TRANSITION RULES

Transition rules, or transition functions, are the most important aspect of CA models. They determine the system evolution; define local patterns and how the system works. The definition of rules depends, among other factors, on the geometry of the grid, the type of neighborhood and the available states (WEIMAR, 1997; SCHIFF, 2011; TORALLES, 2013; SIMÕES, 2016).

Some works apply a classification to rules, similar to what is done with neighborhoods, although the nomenclature is not as standardized. Some examples can be cited:

- Totalistic: the next state depends on the sum of the states of the neighborhood cells; and External Totalistic rules, which also consider the cell being updated (SIMÕES, 2016; ILACHINSKI, 2001);

- Additives: use linear functions of the neighborhood cells (ILACHINSKI, 2001);
- Multiple Steps: rules are divided into sub-steps (SIMÕES, 2016);
- Probabilistic: are evaluated according to calculated probabilities (WEIMAR, 1997).

Traditionally, transition rules are fixed along the simulation and are applied to all the cells in the grid. In general, the major changes made in the classic CA model are in the form that transition rules are created (TORRENS; O'SULLIVAN, 2000); some examples include characteristics as hierarchy, self-modification, probabilistic expressions, exogenous links, weights and randomness.

The rules used in CA models for city simulation can be derived using automatic procedures, although this is not a common solution (LIU et al., 2007). Li and Yeh (2001) proposed a model that uses Neural Networks to define transition rules, requiring information only for simulation training. Feng et. al. (2011) used the Particle Swarm Optimization to improve transition rules identified by statistical methods. Other forms of discovery include the Ant Colony algorithm (LIU et al., 2007) and a variation of the concept (YANG et al., 2013).

4 CELLULAR AUTOMATA IN URBAN MODELLING

Cellular automata are dynamic spatial models, which can describe the evolution patterns of a system through time. They are able to reflect the complexity of systems being studied, mimic their behaviors and help to understand them (BENENSON; TORRENS 2004).

The components of a System can be divided into three categories (ROCHA, 2012):

- elements: constitutes the system (i.e. as sand grains on the beach);
- attributes: the elements characteristics (i.e. color or size); and
- relationships: the associations between elements and attributes.

Most of the systems have common characteristics: structure defined by parts and processes; reality generalizations; the tendency of generating patterns, depending on the inputs, outputs and the process to be transformed; and the functional and structural relations (ROCHA, 2012).

In a city the relation between the man-made, the social and the environmental components frame the complexity and the dynamic of the system (KASANKO et al., 2006). The emergence on the concept that urban systems are almost critically self organized, but far from equilibrium, given its behavior, as the components are constantly changing, but the city itself remains in its place (ROBERTS; KANALEY 2006; BAI, 2007; GRIMM et al. 2008; BAYNES, 2009).

An urban model represents the city so that its aspects and relations can be easily understood, and this may aggregate new information to complexity studies. Mathematical and theoretical models have been used aiming the reduction of the intricacy of urban aspects, to overcome the challenge of the development of urban models (POLIDORI, 2005; HAINES-YOUNG; PETCH, 1986; WADDELL; ULFARSSON, 2004; TORRENS; O'SULLIVAN, 2000).

Models are composed by a number of elements, and the relations of them with its components have distinct levels of intensity and exchange of energy/information. The task of modeling this kind of system may use mathematical formalism, and one or more theories, based on a definition of the real aspect which is being captured (ROCHA, 2012). Computer models processes manipulate information and can generate a set of outputs to reflect the logic behind the model development (BATTY;

STEADMAN; XIE, 2006). Every model about a phenomenon aims to answer questions, as “How this process evolves?”, “Where the phenomenons are?” and “What is behind this phenomenon, which variables influence it?” (LAMBIN, 1994).

Cellular automata models are a common choice in urban simulation, representing the development of a city in time and space, allowing the study of “what if” scenarios. Their application includes studies of traffic, urbanization and land development (TORRENS; O'SULLIVAN, 2000). They are usually chosen for this subject given the simplicity of modeling, the dynamic processes focus and the factors around those processes (LIU, 2008; BASTOS, 2007). Cells are natural representations for city blocks or individual buildings, and have dependency on the neighborhood. Also, CA can reflect self-organization properties (KRAFTA, 1999).

The standard CA needs some modifications in order to fit the simulation of an urban system. This includes additional functionalities, usually used to explore the spatial complexity, test theories and ideas. These changes require strong calibration techniques to establish the model (TORRENS; O'SULLIVAN, 2000).

CA are highly adaptable, may be compatible with geospatial data sets and can be integrate with Geographical Information Systems (GIS), as they are inherently spatial (WHITE; ENGELEN, 2000). GIS data can be used as initial parameters for a CA model, and simulation results can be fed back into GIS to be analyzed (CLARKE; GAYDOS, 1998). CA models complement GIS systems thanks to the ability to handle non deterministic aspects and to perform interactive cycles of simulation (TENODÓRIO et al., 2006).

In order to employ CA in urban studies, the cell contents must be defined, as well as their possible states and the neighborhoods. Also, to define the transition rules and the randomness level, it is important to have knowledge of city history (BATTY, 1997). As hypothetical examples of transition rules can be cited (LIU, 2008; COSTA, 2010):

- Rule 1 - development of a residential area:
  if three or more cells are developed then a not urban cell became urban
- Rule 2 - influence of roads:
  a main road in an area increases the probability of development.

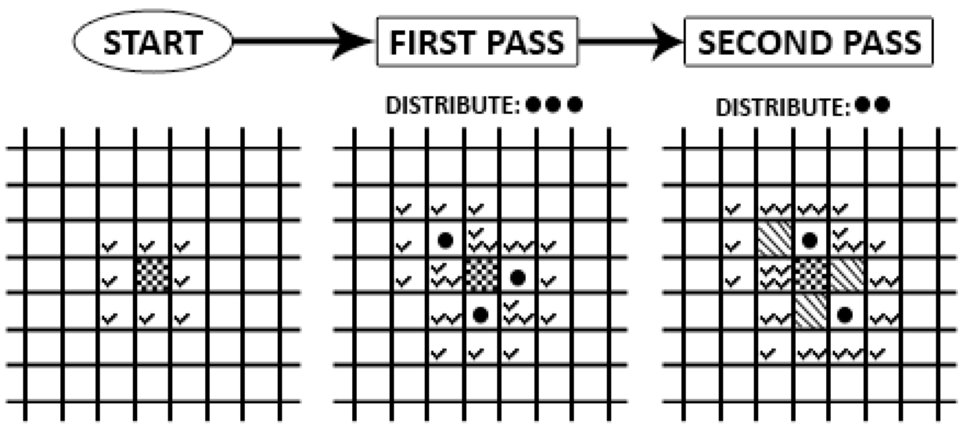
CA has also limitations. They can be affected by the data errors, as positional imprecisions, mistaken attributes and unstable conditions. Errors in the model structure or logic will be propagated through the simulation process. These issues should remind that simulations are just approximations and results may not coincide with the real world (LIU, 2008).

4.1 PREVIOUS WORK

Cellular automata in Urban Modeling started to be used around the 1950s. At this time, the CA research was in the beginning, and the urban researchers were building models to analyze the spatial patterns in the systems (BATTY; COUCLELIS; EICHEN, 1997).

The first known applications of CA in urban and social studies became known around the 1960s, although some concepts appeared still earlier. Torsten Hagerstrand studied an innovation-diffusion model using the neighborhood notion (HAGERSTRAND et al., 1968). Lathrop and Hamburg (1965) developed a model based on cells to simulate the New York State. Chapin and his colleagues from University of North Carolina worked around the notion of flow linked to residential development (CHAPIN; WEISS 1968). One of these examples can be seen in Figure 10, which represents Chapin and Weiss work, showing a flat residential area development, indicating the distribution sequence of new houses by a randomized process.

Figure 10 - Sequence of distribution of residential households



Source: Adapted from Chapin and Weiss (1968).

Possibly the first official CA model was proposed by Waldo Tobler in 1979, for the simulation of urban grow in the city of Detroit. Among the first models, one that caught attention was the work from Couclelis, 1985, who tried a different approach and developed a model based on the "Game of Life". Despite this, his simulation was not considered realistic, just a metaphor of urban growth (LIU, 2008; SANTÉ et al., 2010; COSTA, 2010).

Around the 1990s a new perspective of models started to appear, when White and Engelen developed a CA model to simulate land use change dynamics (WHITE; ENGELEN 1993; LIU, 2008). Some of these “new era” models are listed in Chart 2.

Chart 2 - CA urban models

Model	Authors	Description
White and Engelen	White and Engelen	Published in 1993, simulates the land use of a hypothetical city. Calculates the transformation transition potential of each cell, using it own state and it's neighborhood, and the transition probabilities in each interaction. Temporal scope between 15 and 25 years (BASTOS, 2007).
SimLand	Wu	Proposed in 1996, combines CA with multi criteria evaluation and analytic hierarchy process on the GIS environment. The cells states can be urban and not-urban, and vary between urbanized, industrial districts a road system. Works with three transition rules, the growth rate and degree of attractiveness are defined by the user (BASTOS, 2007).
CLUE-S	Veldkamp and Fresco; Verburg et al.	The conversion of land use and its effects uses the combination of empirical analyses and dynamic simulation of competition/interactions between spatial and temporal dynamics of the system to simulate land-use changes (VERBURG et al., 1999; VELDKAMP; FRESCO, 1996)
UGM model	Clarke	An urban growth model developed in 1997. Uses four variables to define the probability of one not-urban cell became urban. These variables are: actual state of the cell, soil slope, proximity of the roads and inclusion or exclusion of the simulation. Also have four kinds of urban growth: organic expansion, diffusion, spontaneous/self generation, and road system influenced. Temporal scope of 100 years (BASTOS, 2007).
SLEUTH	Clarke and Gaydos	Proposed in 1998, the model was built to simulate the Bay Area, and started the project Gigalopolis. This model is used to the development of this work and will be better described in the follow section (COSTA, 2010).
FCUGM	Al-Ahmadi et. al	The Fuzzy Cellular Urban Growth Model was developed by Al-Ahmadi et. al, and published in 2008. The model involves fuzzy logic and fuzzy set theory to capture the transition rules probabilities (AL-AHMADI et al., 2009).
TerraME	Federal University of Ouro Preto;	It is a multiparadigm modeling toolkit where the user can choose the different parts of the model (behavior, time, and space). Also, enables the combination of agent based, CA, SD and discrete

	National Institute for Space Research	event simulation paradigms. Was developed by the Federal University of Ouro Preto and the National Institute for Space Research, both from Brazil (CARNEIRO et al, 2013).

Source: Own Authorship.

Besides the examples of Chart 2, there are also studies that make use of generic tools as Matlab (TAYYEBI; PIJANOWSKI; TAYYEBI, 2011; GUAN; WANG; CLARKE, 2005) or Netlogo (LAGARIAS, 2012).

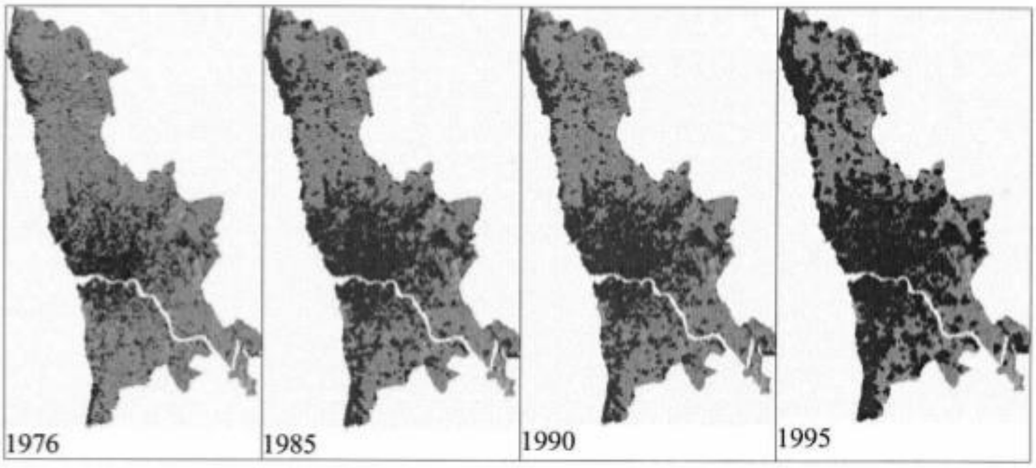
The Remote Sensing Center of the Federal University of Minas Gerais also developed simulation software called DINAMICA. It implements features that support CA models for geographical simulation, being freeware, but closed source. It is important to point out that in addition to these, there are several others tools and models used for urban simulation.

Among the tools available, SLEUTH seems to be the most widely used in the field, and it is free and open source. This model is adapted to different scenarios by adjusting the spatial accuracy and the scale sensitivity (SANGAWONGSE; SUN; TSAI, 2005). It can generalize and mirror the characteristics and the individuality of the region, and reveal new emergent particularities (SILVA; CLARKE, 2005). Besides modeling urban growth, it has also been employed to analyze how urban areas dominate land and produce natural impacts (United States Environmental Protection Agency, 2000 apud SANGAWONGSE; SUN; TSAI, 2005).

4.2 SLEUTH MODEL

SLEUTH probably is the most popular CA model to simulate urban growth. Developed using C language around 1997/1998 by Clarke, was created to predict land use in the San Francisco Bay Area. In this project it was used the Linux version, released in 2005. Its name is an acronym of the input layers used in the model: Slope, Land Use, Excluded Areas, Urbanization, Transportation and Hillshade. Runs in UNIX or UNIX-Based operating systems, includes the urban growth model (UGM) and the deltatron land use model (DLM) (RAFIEE et. al, 2009; DOUKARI et al., 2016). An example of the SLEUTH model can be seen in Figure 11, which shows the work developed by Silva and Clarke (2005) simulating the land use in the city of Porto, Portugal.

Figure 11 - Urban Evolution of the Metropolitan Area of Porto - Portugal



Source: Silva and Clarke (2005).

The SLEUTH model incorporates the main characteristics of the CA model: a grid space of homogeneous cells, a neighborhood of eight cells, two possible cell states (urban/non-urban), and transition rules that work in sequential time steps. As it is a model developed for urban growth, some specific features were added to it (CLARKE; HOPPEN; GAYDOS, 1997; SILVA; CLARKE, 2005):

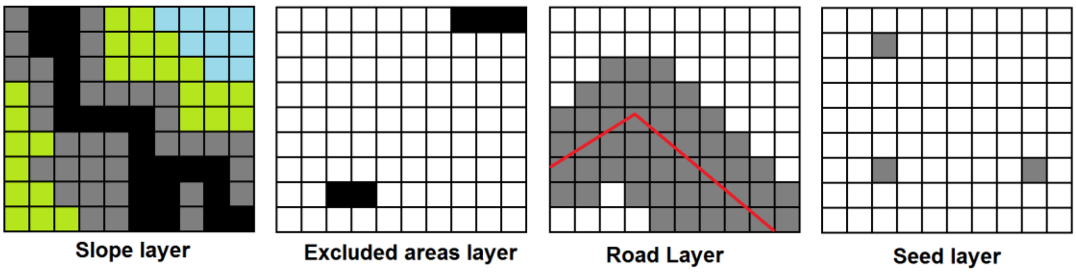
- weight for cells: is possible to define how much a cell has influence on the urban growth by the color applied to that. The most influence has a cell, higher should be your value translated in color. As an example, in the roads layer from this project, the highways should be colored with white, and the neighborhood streets, with less influence, should be closer to black;
- self-modification mechanism: allows rules to change when some behaviors are detected by perceiving the environment, this includes the location, neighborhood, land type and probabilities. The metrics are regulated by the self modification parameters; this happens when a growth boost happens or when the city growth declines significantly.

SLEUTH has an automated calibration procedure, where the model parameters and constants are estimated and adjusted seeking refined results. The model can adapt to the main characteristics of the system using the history of the city as a basis to calculate them, what make possible the transitions between intense rapid growth to little or no growth. These are the characteristics make possible the creation of a simplified copy from the urban behavior (SILVA; CLARKE, 2005).

The tool requires the input of four different layers (Figure 11) (CLARKE; HOPPEN; GAYDOS, 1997):

- Seed Layer: is the initial distribution from the urban areas, represented by the gray cells in Figure 12 - Seed layer. This data can be hypothetical or historical. To execute the model, is necessary to have at least four time cycles available for statistical calibration;
- Slope Layer: used to regulate the weight of the slope-resistance. The layer is the result of the interpolation of a digital elevation model converted to a slope for every cell. In Figure 12 - Slope layer, the different colors represent different percentages of slope;
- Excluded Areas Layer: identifies the cells that are not part of the growth process, including hydrographic regions, oceans and protected areas, it is represented by the black cells in the Figure 12 - Excluded areas layer;
- Roads Layer: describe the roads at certain periods of time, represented by the red line in Figure 12 - Road layer; and uses a binary array to work. It has a buffer defined by the road gravity, control factor and defining the road attractiveness for development.

Figure 12 - Input data layers used by SLEUTH model



Source: adapted from Clarke; Hoppen; Gaydos (1997).

SLEUTH execution follows five steps: model compilation, data input preparation, calibration, prediction and result output (YANG; LO, 2003). It starts reading the input layers, and initializing random numbers. An exterior loop analyzes the location growth 'history', to retain all the necessary data to perform the calibration phase. An interior loop compiles the CA and the growth rules for one cycle. Finally, the descriptive data is saved into a file used in the next calibration phases (CLARKE; HOPPEN; GAYDOS, 1997).

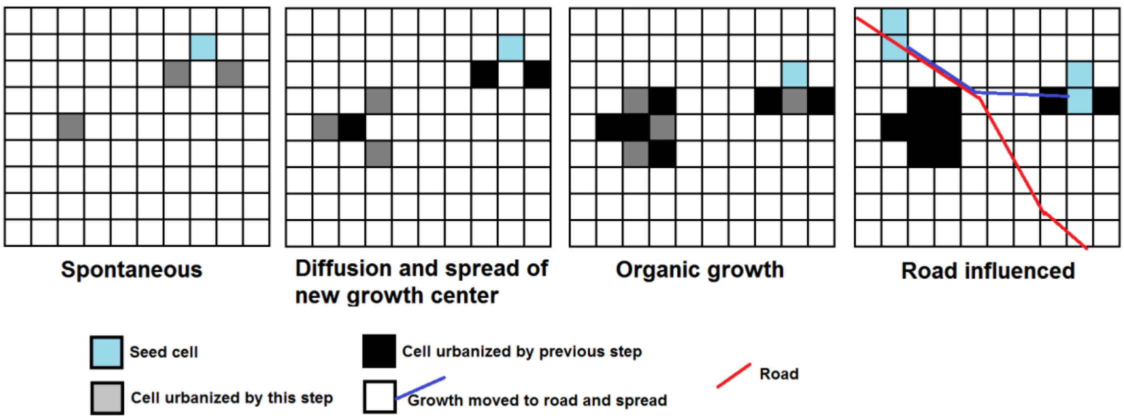
The model is controlled by five factors (CLARKE; HOPPEN; GAYDOS, 1997; SILVA; CLARKE, 2005):

- Diffusion: define how the cells will be distributed and how the new settlements are going to move through the road system;
- Breed: determines how the new settlements begin their own growth cycle;
- Spread: decide how is going to happen the 'organic growth' expansion outside and the system will be filled inside;
- Slope: influences the probabilities of steeper slopes have settlements;
- Road Gravity: simulate the attraction of settlements to the road system.

For SLEUTH the city is like a living organism, the model tries to replicate the transitions in the maps, and mimic the historical data, by computing its parameters (CHAUDHURE, CLARKE, 2013). Accordingly to Doukari et al., the spread factor is the coefficient with more influence in the model response variability. Using these factors, four different types of growth are allowed, they are defined as the growth rules, illustrated in Figure 13 and explained bellow (CLARKE; HOPPEN; GAYDOS, 1997):

- *spontaneous new growth:* a location is randomly chosen and if it has one not urban cell that passes the slope test, it becomes a new urban location;
- *diffuse growth and spread of a new growth center:* cells that passed in the diffusion test and the slope test, which means that they are reasonably flat, are urbanized;
- *organic growth:* an area with three neighbors, that passes the spread slope test, becomes a new urban center;
- *road influenced growth:* a random place, where is possible to find a road in given a distance, is moved to the road and spread to become a new growth.

Figure 13 - SLEUTH Growth rules



Source: Adapted from Clarke; Hoppen; Gaydos (1997).

As already been said, when the simulation detects intense growth or little/no growth the control parameters change. Intense grow, leads to the Diffusion, Spread and Breed factors to increase, what encouraged the tendency of an expanding system. When the contrary happens, this factors change to what look like to a depressed area (SILVA; CLARKE, 2005).

The calibration is performed using Monte Carlo simulation to record the history of the urban growth and is based in the phases: coarse, fine and final. First, hierarchical spatial resolutions are used to adjust the parameters that are related to the growth, and then a finer resolution is used to adjust the distinct parameters. After finding the range for the historical data, the calibration is repeated two times, what results in a narrower range of parameters (DIETZEL; CLARKE, 2007). Basically, the model calibration should be executed three different times, using different image sizes. The coarse phase should use images with ¼ of the full size, and the coefficients must include all the available range (0 - 100). The second phase, called fine, should have images with the half of the size of the full size images and the coefficients must be defined using the range with better results achieve in the first calibration phase. In the final phase, the range used is even more refined, as it is a result from the fine step, and the full resolution images are used.

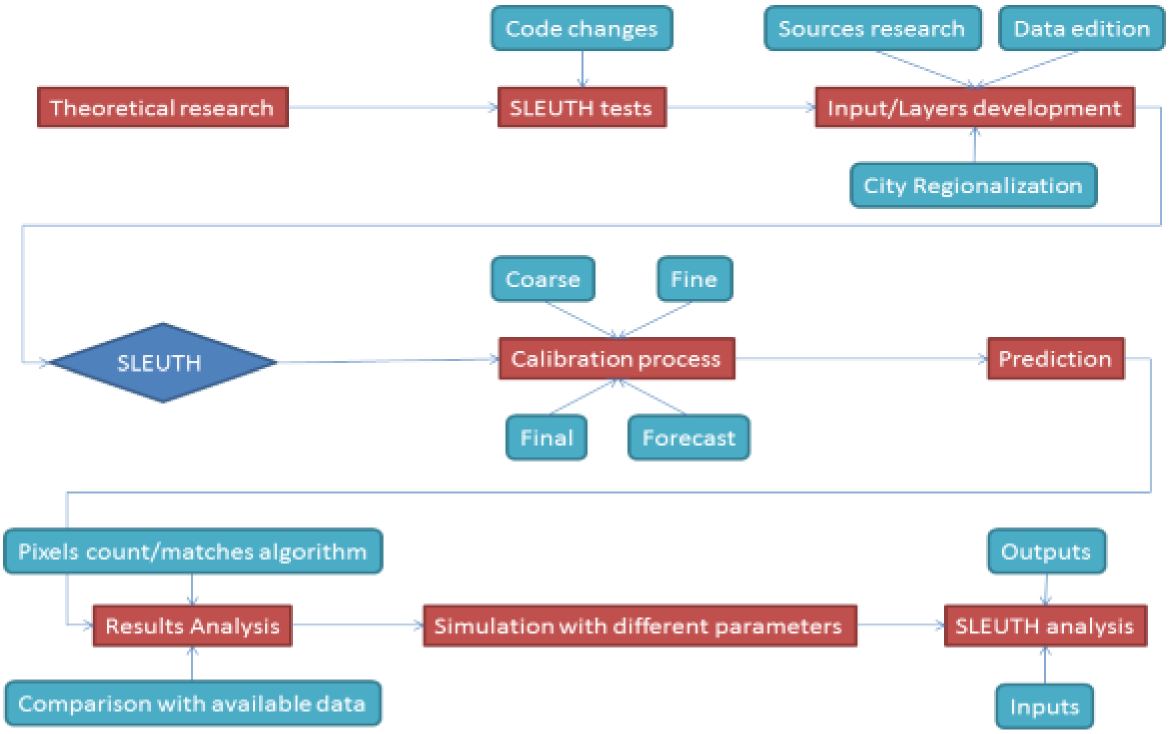
In each phase, the results of the metrics are ordered, and the ones that synthesize the system behavior, are extract to the next phase. The four maps with different information, 13 metrics, and the interaction between then, create a set of thousands of different combinations for each cell. The combinations that reflect the growth rules are tested in a simplified space, resulting in refined values, which will be tested again in a more detailed space, successively. Thus the characteristics are adjusted saving processing time. The variations between phases verify the behavior of the elements, their performance in different scales, their development, their variations and their importance on the system (COSTA, 2010). These phase improves the simulation and the data used, giving the possibility to run a simulation closer to the real world (SILVA; CLARKE, 2005).

As any simulation model SLEUTH has some limitations that worthy be discussed. The model is very time consuming, and has a calibration process sensitive and subjective. It has difficulties to simulate growth that is not originated organically, and sometimes the randomness and cumulative probability may affect the model performance (WU et al., 2009).

5 DEVELOPMENT

Figure 14 represents workflow of this project. It began with a review of literature related to urban phenomena and the cellular automata models. Following the bibliographic research, a practical study of SLEUTH took place. The tool was installed and tests were executed in order to understand the various parameters and data sources involved.

Figure 14 - Project workflow



Source: Own Authorship

When the tests started, crashes were observed. The flaw, a string overflow, was found in 'landclass_obj.c':

```
char zeroes[] = "000000";
char hex_str[6];
strcpy (hex_str, zeroes);
strcpy (hex_str + 6 - strlen (color_str), color_str);
```

The first successful test with SLEUTH was in May/2018. The calibration process took 45 hours, divided into 3 hours for coarse calibration, 16 hours for fine and 26 hours used in the final phase.

5.1 STUDY AREA

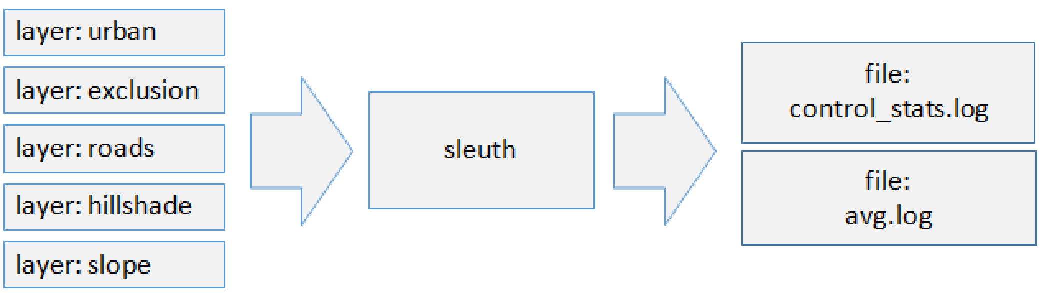
Ponta Grossa is a Brazilian city, located in the south state of Paraná. Its origins go back to 1700, when the region was traversed by cattle merchants. The city was recognized as such in 1862. It has been the destiny of many immigrants, and today it is mainly known as a convergence point of many roads (Prefeitura Municipal de Ponta Grossa, 2018).

It has an average altitude of 975 meters, and a total is of 2054,735 km². Accordingly the census population estimate of 2014, the city had 334535 inhabitants. These years was used in the calibration process, to compare the SLEUTH forecasting for 2017 with the real data available. The city borders with Palmeira, Teixeira Soares, Campo Largo, Tibagi and Ipiranga. Has an extensive hydrographic network and the economy is based on several activities, as industries, agriculture and tourism.

5.2 DATA PREPARATION

SLEUTH depends on a set of input files, corresponding to the layers that form the SLEUTH acronym: topographic Slope, zones Excluded from growth, Urban spatial extent, Transportation networks, terrain Hill shading, and categories of Land Use; this last one is not mandatory and was not considered in this project. All these layers are represented as gif images. The tool requires a minimum of four images of urban areas in different periods and two maps of roads in different dates. It outputs several log files, the two most important being represented in Figure 15.

Figure 15 - SLEUTH inputs and outputs



Source: Own Authorship

The files used in the study have 1242x1339 pixels, with a spatial resolution of 30 meters per pixel. The non-urbanized areas of the city were removed. The city hall does not keep city historical data, so in order to prepare layers for SLEUTH, information from IPLAN (Instituto de Pesquisa e Planejamento Urbano de Ponta Grossa), Google Earth, and INPE (Instituto Nacional de Pesquisas Espaciais) were collected. This includes GIS digital data sources, satellite images, and topographic maps.

A road layer for 2017 was built with the help of the software Quantum GIS (QGIS), extracting data from the OpenStreetView project with a plug-in called Open Layers. Several images were obtained this way, but there were differences between them with respect to the roads. A few important streets were not present and had to be added manually in the images. In order to delimit the city borders and extract just the information of interest it was used a shape file from the IBGE (Instituto Brasileiro de Geografia e Estatística) database, which contains the Brazilian cities administrative borders.

Due to the lack of historical files for roads, layers for previous years were constructed by hand. The manual procedure consisted of erasing from the current map the streets which did not exist on 1984 and 1996, according to satellite images. In all road layers, isolated streets, without connection to other roads, were deleted.

Roads layers in SLEUTH employ shades of grey for classification. In this project, roads connecting to other cities were painted with the highest value (100); avenues and streets that connect the neighborhoods to these roads and have a substantial impact were marked with the intermediate value (50). Other streets have the lowest value considered (25). These values are indicated in the documentation. The resulting image can be seen in Figure 16.

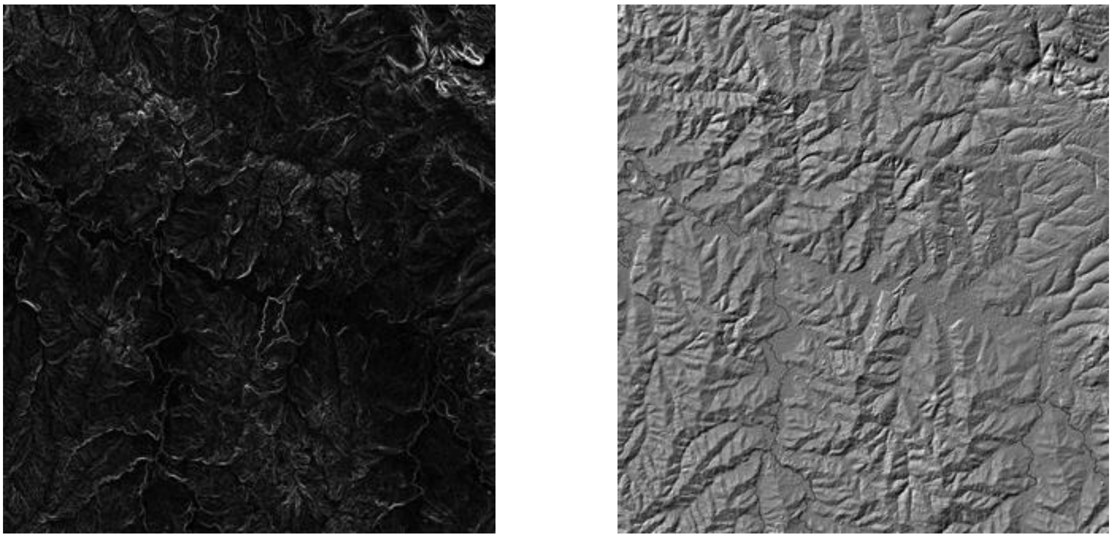
Figure 16 - Roads Layer

Source: adapted from OpenStreetView

To create the layers Slope and Hillshade, four tiff images were downloaded from the Aster Global Dem (ASTER GDEM) dataset in Earth Explorer site. ASTER GDEM is a product of METI and NASA and contains the Digital Elevation data collected by the Aster instrument on the Terra satellite.

The images were opened on the QGIS software and Hillshade and Slope data were extracted using the Analysis of DEM option. It is worth mentioning that, as SLEUTH uses the color on the Slope image to identify the degree of inclination, the image was extracted using the percentage option instead of the degree expression. The slope and hillshade images can be seen in Figure 17.

Figure 17 - (a). Slope Layer; (b). Hillshade



(a) **(b)**

Source: adapted from Earth Explorer/ASTER GDEM

The excluded area layer represents regions where growth is not possible or not allowed. It was based on the Municipal Director Plan developed in 2001 by the Ponta Grossa IPLAN (Institute for Research and Urban Planning). From this document, it was used the Conservation Unit section and the image available in the official site from the Institute. The regions represented in this layer correspond to the Campos Gerais National Park, Vila Velha State Park, Environmental Protection Area of the Devonian Escarpment and Tibagi River Wildlife Refuge. Cities surrounding Ponta Grossa were also added in this layer. The result is shown in Figure 18.

Figure 18 - Excluded Areas (White: excluded - black: not excluded)

Source: adapted from Municipal Director Plan - 2001

Urban layers representing the city footprint were developed manually, using data downloaded from Google Earth, which uses Landsat and CNES/Airbus data, and aerial pictures from INPE (Instituto Nacional de Pesquisas Espaciais). Urban areas were identified visually and colored manually (Figure 19).

Figure 19 - Urban Area identification

Before identification **After identification**

Source: adapted from Google Earth

The urban layers were separated by a difference of three years. The available images were overlapped to compare urban spots and help the identification of urban and not urban areas. Some zones were difficult to classify; one example of this issue can be seen in Figure 20.

Figure 20 - Undecidable / unrecognized area

Source: adapted from Google Earth

Next, the images were overlapped to check the urban borders. This was necessary because the images had different levels of quality. One of the layers resulting from this approach can be seen in Figure 21, corresponding to 1984.

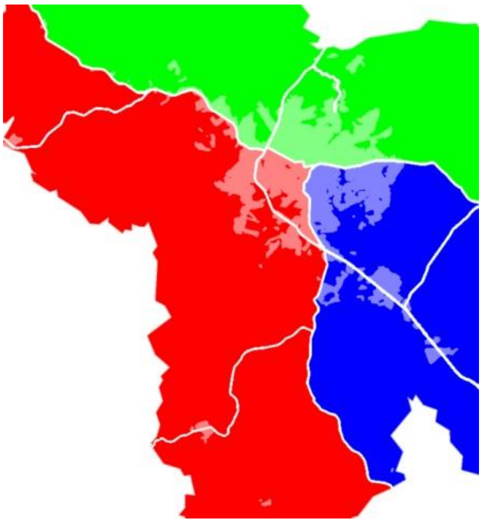
Figure 21 - Urban layer, 1984 (White: urban - Black: not urban)

Source: Own Authorship

5.3 CITY REGIONALIZATION

In the next phase of the project, simulation was performed with separated city regions, and different images for exclusion layers had to be prepared. Different approaches were initially considered for the city regionalization, as using a simple square division, or by area size. The chosen regionalization was based on a few criteria, related to the position of highways and important streets, social aspects and the neighborhood shape (Figure 22). Brazilian cities adopt a ‘neighborhood division’ (bairros), useful for postal code definition and localization. It is quite usual that such ‘bairros’ show distinct socioeconomic differences. In order to localize neighborhoods, a shape file was downloaded from IPLAN, corresponding to the city neighborhoods in 2008.

Figure 22 - Regionalization of the city

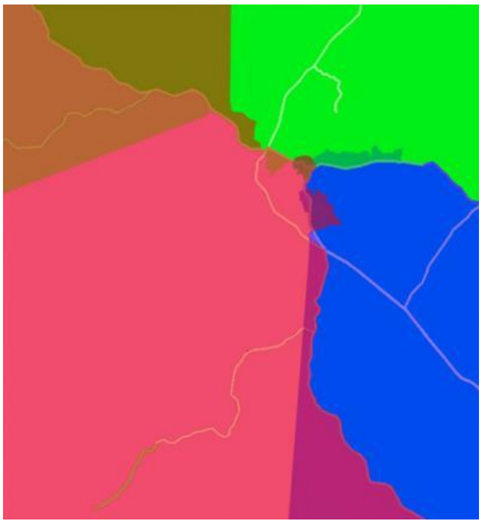


Source: Own Authorship

The map was divided into three large areas that have a certain level of independence: all three areas in Figure 22 have pharmacies, markets, banks, and stores. The city center is inside all the subdivisions and, far neighborhoods of Oficinas and Periquitos make part of two regions each one.

A small overlap was set between neighbor regions, to permit interactions between them as diffusion and organic growth in SLEUTH. The overlap can be seen in Figure 23, represented by brownish and purplish colors.

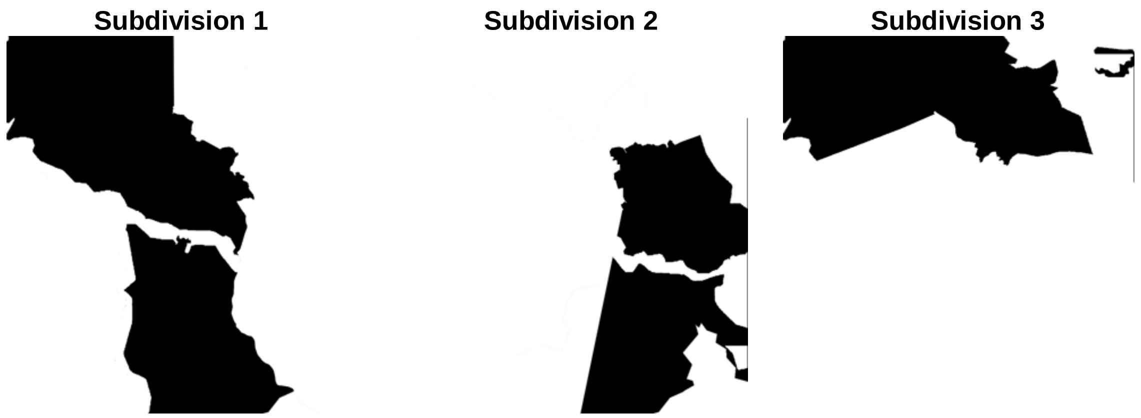
Figure 23 - Overlap between subdivisions



Source: Own Authorship

Two different approaches were used for calibration and simulation. In the first one, only the excluded areas were modified. The exclusion layer of each experiment contained just the region available for growth. The resulting images can be seen in Figure 24.

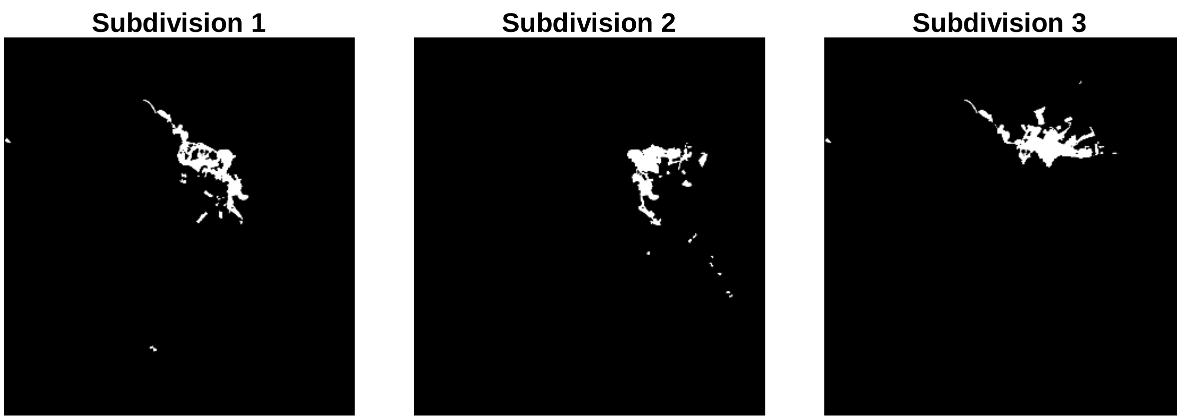
Figure 24 - Excluded layers of each subdivision



Source: Own Authorship

In the second approach, the urban layers were modified, and regions were painted with black to remove parts of the city. The reason for doing this was to observe the behavior of SLEUTH with regard to calibration. In the Figure 25 below is possible to see the layers used for the year of 1984 in each subdivision.

Figure 25 - 1984 urban layers for each subdivision



Source: Own Authorship

There were a total of eighteen .gif files for the first round of calibrations, and fifty six for the second. They are:

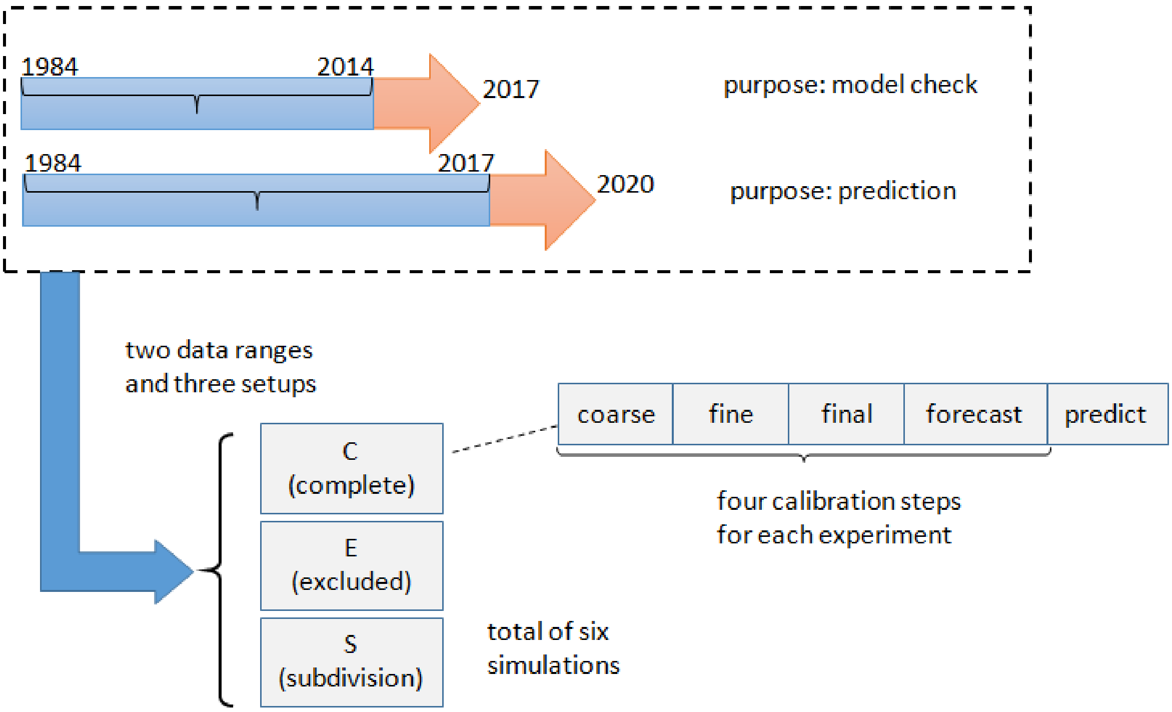
- One slope layer;
- One hillshade;
- Three roadmaps;
- Four excluded area maps;
- Forty eight urban spots.

5.4 CALIBRATION AND PREDICTION PROCESS

The experiments were performed using two different time intervals: from 1984 till 2014, and from 1984 till 2017. The first time interval (1984 - 2014) chosen as it allows the comparison between SLEUTH forecasting results with the real data available (2017) and the second to observe how the model predicts the near future (2020).

In addition to the use of two time intervals, the simulation was executed using the three different setups for exclusion layer explained in the previous section, for a total of six sets of results. Each of these six sets involved four rounds of calibration (Figure 26), following the procedure recommended in SLEUTH documentation, totaling 14 different simulations.

Figure 26 - Calibration process



Source: Own Authorship

The coarse calibration is the first phase of the SLEUTH calibration process. During calibration, the tool performs several simulations while the values of the five parameters (spread, diffusion, slope, and road) are varied within a prescribed range. For the coarse process, the images had only one quarter of the full size, or 310x334 pixels. The parameters were varied from 0 to 100 in steps of 25 units. Each combination of parameters was used in five runs of Monte Carlo simulation. These parameters are recommended in SLEUTH documentation. This calibration step took approximately 36 minutes in a computer with 6 GB of RAM, core i3 processor and a CPU of 2.20 GHz.

For the fine calibration, the scenario file was configured to run eight Monte Carlo simulations, with input files that had half the full size images, or 621x670 pixels. The SLEUTH logs derived from the previous phase are used to define the scenario coefficients. The control_stats.log file contains the results of all simulation runs: 5 Monte Carlo simulations to calculate the output for each combination, for a total of $5^5 = 3125$ results.

The parameters are chosen according to the metrics computed by SLEUTH. Using a spreadsheet editor, the control_stats.log was organized and the results sorted in decreasing order using the chosen metric.

In the present study it was used the Lee Salle metric. The range selected for the parameters was based on the top 10 results. In this phase, the difference between the start and stop values was at least 25. The step was defined by the result of the subtraction of the start and stop values divided by 5. In this phase, the calibration took near to 7 hours to finish.

In the final phase, the preceding steps were executed once again. There was more than 6000 simulation runs, depending on the scenario, and only the top six results were considered. For the final calibration, the difference between step and stop was minimum 5. The number of Monte Carlo simulations was raised to ten and the images used had 1242x1339 pixels. This calibration phase took approximately 38 hours to complete.

A fourth calibration is performed in order to execute the Prediction for the city. It is known in SLEUTH documentation as ‘forecasting calibration’; this step derives the Prediction coefficients, also known as Best Fit. To execute the forecasting, the number of Monte Carlo simulations was raised to 150 and the full size images were used. The coefficients were defined using the result with the highest Lee Saale metric in the control_stats.log derived from the Final calibration. In this scenario, the start and stop values were the same, and the step was set to one, meaning that a single set of coefficients would be considered.

For the Prediction step, the number of working grids was raised to six. The number of Monte Carlo simulations was the same used in the Forecasting calibration

(150) and the full size images were used again. The coefficients for this run were defined by the file avg.log, derived from the forecasting calibration. The values of coefficients corresponding to the Stop Date, last year available, are selected, rounded and informed in the scenario as the Best Fit values. Also, the prediction dates, were defined: the start was 2014 or 2017 (two data ranges were used) and the stop date was set as 2017 or 2020, respectively.

The coefficients used in the calibrations and in the Prediction, can be visualized in Table 1; the results will be detailed in the next section. As a way to simplify the reading , the simulations will be identified as follow: C, for the simulation using the whole map; E, when only the Excluded Layer was modified to represent each region of the city; and, S, when the city map was also modified to select only a subdivision for analysis.

Table 1 - Coefficients used in the simulations

	Comp - 2014	Comp - 2017	Excl 1 - 2014	Excl 1 - 2017	Sub 1 - 2014	Sub 1 - 2017	Excl 2 - 2014	Excl 2 - 2017	Sub 2 - 2014	Sub 2 - 2017	Excl 3 - 2014	Excl 3 - 2017	Sub 3 - 2014	Sub 3 - 2017
	Fine	**Fine**	**Fine**	**Fine**	**Fine**	**Fine**	**Fine**	**Fine**	**Fine**	**Fine**	**Fine**	**Fine**	**Fine**	**Fine**
Diffusion	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25
Breed	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-25	0-50	0-25	0-25
Spread	75-100	75-100	75-100	75-100	75-100	75-100	75-100	75-100	75-100	75-100	75-100	75-100	75-100	75-100
Slope	0-25	0-25	0-25	0-25	0-25	0-25	50-100	0-50	0-100	0-100	0-25	25-50	50-75	25-50
RG	0-100	0-100	0-100	0-100	0-100	0-100	0-100	0-100	0-100	0-100	0-100	0-100	0-100	0-100
	Final	**Final**	**Final**	**Final**	**Final**	**Final**	**Final**	**Final**	**Final**	**Final**	**Final**	**Final**	**Final**	**Final**
Diffusion	0-5	0-5	0-5	0-5	0-5	0-5	0-10	0-10	0-5	0-5	15-20	0-5	0-10	0-25
Breed	5-20	0-25	20-25	20-25	5-15	5-25	0-15	20-25	0-5	5-10	15-20	30-35	10-20	10-15
Spread	95-100	95-100	95-100	95-100	95-100	95-100	95-100	95-100	95-100	90-100	95-100	95-100	95-100	95-100
Slope	20-25	20-25	0-5	0-5	5-10	0-10	50-55	0-5	20-25	20-25	0-5	25-30	50-55	25-30
RG	25-100	0-50	0-100	0-100	0-100	0-75	0-75	0-100	0-100	0-100	0-75	0-100	0-50	0-100
	Fore	**Fore**	**Fore**	**Fore**	**Fore**	**Fore**	**Fore**	**Fore**	**Fore**	**Fore**	**Fore**	**Fore**	**Fore**	**Fore**
Diffusion	2	5	1	1	4	5	1	4	1	5	15	1	1	1
Breed	14	25	23	24	7	25	12	24	4	5	17	31	20	13
Spread	100	100	100	98	100	99	100	99	100	100	95	100	100	100
Slope	20	20	1	1	5	1	50	1	20	20	1	25	50	25
RG	40	40	25	25	50	15	1	75	50	1	1	1	1	1
	Predict	**Predict**	**Predict**	**Predict**	**Predict**	**Predict**	**Predict**	**Predict**	**Predict**	**Predict**	**Predict**	**Predict**	**Predict**	**Predict**
Diffusion	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Breed	1	1	1	1	0	1	1	1	0	0	1	1	1	0
Spread	5	3	5	3	5	4	5	3	6	5	4	3	5	3
Slope	100	100	100	100	100	100	100	100	100	100	100	100	100	100
RG	27	26	0	0	27	0	1	1	1	1	1	1	1	1

Source: Own Authorship

6 EXPERIMENTS RESULTS

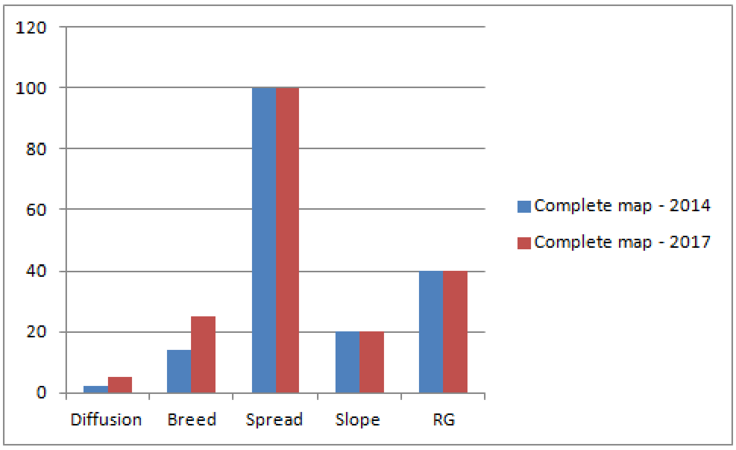
By observing the parameters obtained in the calibration processes, it was possible to get a general picture of how the SLEUTH model tries to assimilate the city of Ponta Grossa. The following sections analyze the results that were computed from the phases of calibration, forecasting, and prediction.

6.1 FINAL CALIBRATION PHASE

6.1.1 Complete Map

The coefficients from the Final phase of the calibration process from 2014 and 2017, for the complete city map, are represented in Graphic 1. The Diffusion and Breed coefficients suggest that the emergence of new urban centers far away from the major urban spot was rare; when that happened, they usually grew slowly, as the values are below 25.

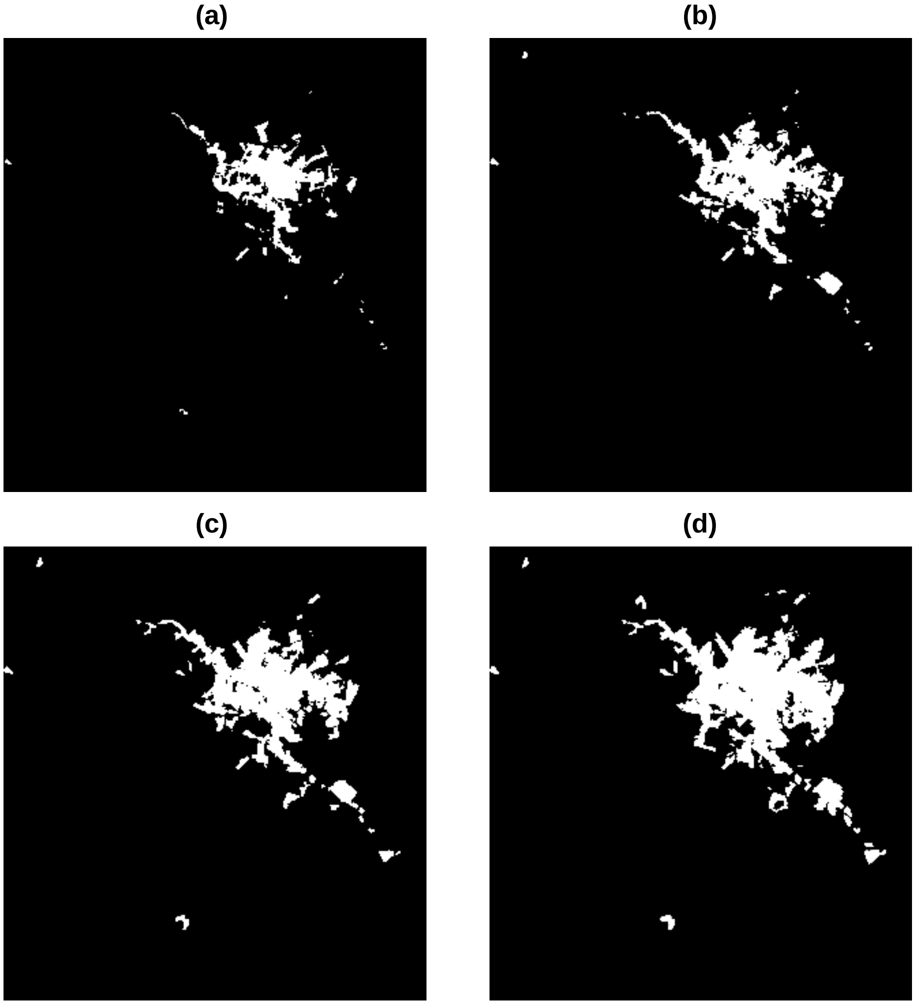
Graphic 1 - Complete Simulation - Final calibration results for 2014 and 2017



Source: Own Authorship

The high value for the Spread coefficient corresponds to a high percentage of organic growth during the analyzed periods. This coefficient was the most significant in the simulation, meaning that the organic sprawl was the major process responsible for city expansion. Figure 27, shows the actual city maps for the years 1984, 1993, 2002 and 2014. Observing the maps it is possible to conclude that the city seems to grow mainly by spreading the existing urban mass, as the organic growth description, agreeing with what was detected by SLEUTH.

Figure 27 - Urban spots from the years (a) 1984, (b) 1993, (c) 2005 and (d) 2014, representing the urban spread



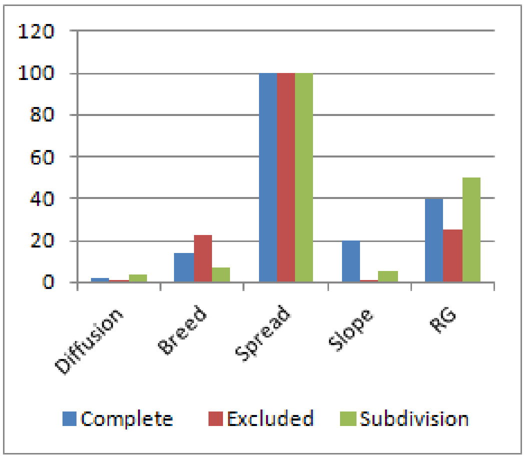
Source: Own Authorship

The Slope resistance coefficient has low values, near to 30. While doing the simulations, it seemed that the Road Gravity coefficient did not have a great influence either. In the final phase results, this coefficient stabilized with a medium rate in 2014 simulation best results. But, it fluctuated in the best results achieved in the 2017 simulation, showing that the difference between its results have low impact in the Lee Salee metric.

6.1.2 Subarea 1

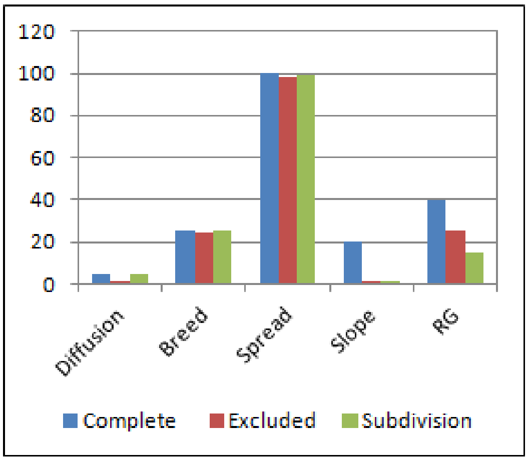
The majority of the results for simulations corresponding to S1 presented the highest rate of organic growth (spread). This can be visualized in Graphics 2 and 3, and means that the city growth happens around areas that are already urbanized. Besides this, the results computed by SLEUTH show that, in this region, new city centers are rare or not existent. Only a few spots appear around the city over the years.

Graphic 2 - Final calibration best results for Subarea 1/2014 approaches



Source: Own Authorship

Graphic 3 - Final calibration best results for Subarea 1/2017 approaches



Source: Own Authorship

The low value of Breed coefficient means that the probability of growth in such areas was low; however, a small change between simulations was detected by the model, and the Breed coefficient rise to 25. This may be the result of the appearance of new spots between 2014 and 2017, what can be visualized in Figure 28.

Figure 28 - Comparison of the same area in 2014 (a) and 2017 (b), showing new urban spots

(a) **(b)**

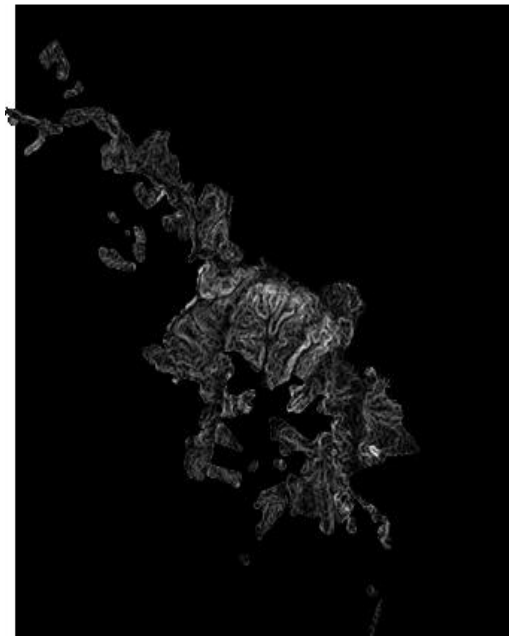
Source: Own Authorship

In the simulations of the first subdivision, the most significant differences occurred in Slope Resistance and Road Gravity. It seems that in the first area analyzed, the slope is less significant than in the rest of the city, meaning that this aspect has little effect on the urbanization. This characteristic can be observed when the slope and urban spot maps are compared. Figure 29, shows the urban spot over the slope map and the slope of this area. The areas with high slope are the lighter ones in the image, and, as can be perceived, some of these regions are urbanized.

Figure 29 - Subarea 1 urban spot superimposed over the slope map (a) and the slope of the urban area (b)

(a)

(b)



Source: adapted from Earth Explorer

The Road Gravity coefficient seems to have a medium impact in urban growth in 2014, with values for the final calibration higher than 25. But in the 2017 simulation the value of this coefficient floated between 1 and 75.

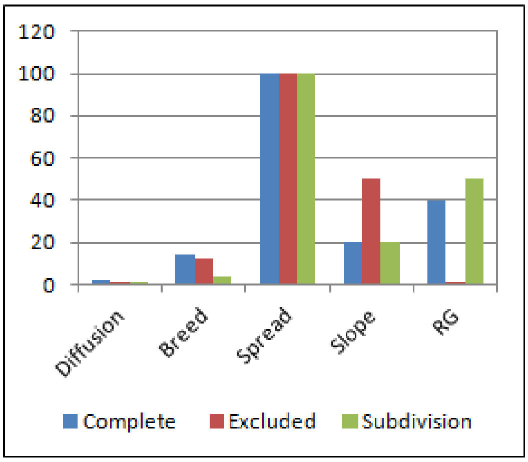
Both Slope and RG coefficients were very different between the exclusion and the subdivision approaches. This may have happened because when the model is calibrated, the excluded areas are ignored by the process, but they are considered in the calculation of the Lee Salee metric. This metric compares the simulated pixels with the real ones. It is computed by dividing the intersection area by the union of the urban areas, as seen in the code of stats_obj.c:

```
static void stats_compute_leesalee (GRID_P Z, GRID_P urban, double leesalee){
        {…}
          for (i = 0; i < mem_GetTotalPixels (); i++){
            if ((Z[i] != 0) || (urban[i] != 0)){
              the_union++;
            } if ((Z[i] != 0) && (urban[i] != 0)) {
              intersection++;
            } }
          *leesalee = (double) intersection / the_union;
          {…}
        }
```

6.1.3 Subarea 2

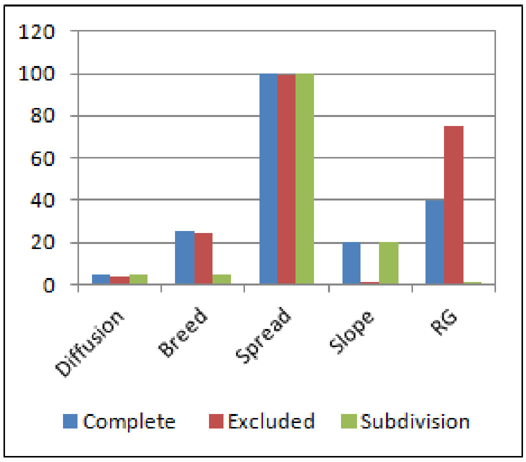
As it happened with the simulations for S1, in S2 the coefficients controlling the occurrence of new random urban centers were low. This is shown in Graphics 4 and 5. The values for spread also repeated what happened with the subarea 1, with high values for organic growth.

Graphic 4 - Final calibration best results for Subarea 2/2014 approaches



Source: Own Authorship

Graphic 5 - Final calibration best results for Subarea 2/2017 approaches



Source: Own Authorship

The bigger differences are seen in the Slope and RG coefficients. In the second subdivision, land declivity has a higher impact in the city growth than in the S1, showing slightly more influence on the way that this area spreads. Road Gravity also seems to have more importance on how urban spots sprawl. In the last phase of calibration, the values for the top results of the RG were above 50, showing moderate relevance. This characteristic detected by SLEUTH matches what is observed in the maps. Figure 30 shows that this area developed mostly around city highways.

Figure 30 - Urban spot overlapped by the roads

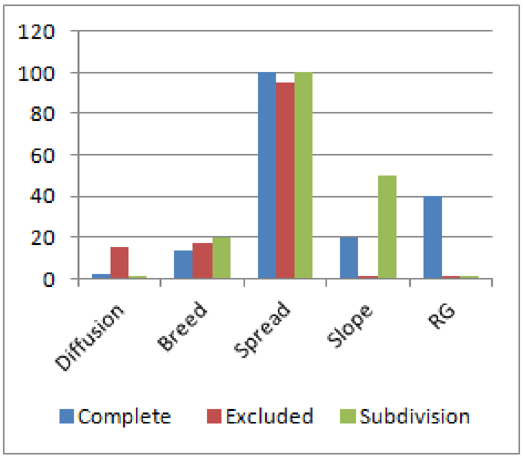
Source: Own Authorship

In the 2017 calibration, the RG coefficient varied between 1 and 100 in the top results. This may indicate that SLEUTH could not narrow the range of this parameter as a function of the growth. Likewise, in the subdivision 1, the excluded area simulation had results very different from the subdivision approach, mainly in the coefficients Slope and RG. In 2014 calibration the Slope was 50 in E and 20 in S, and in 2017 it was 1 in E and 20 for S. The RG results also had mixed patterns, in 2014 the E top result was 1 and S 50, in 2017 E was 75 and S 1.

6.1.4 Subarea 3

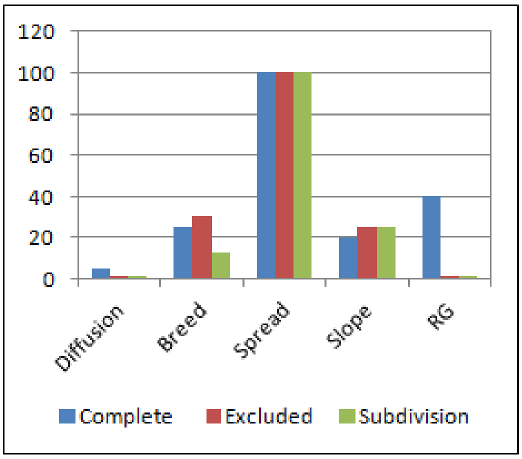
This subdivision repeated previous with high percentage of organic growth and little chance of creation of new urban centers randomly. The values are shown in Graphics 6 and 7. The probability of these new urban centers develop slightly change between 2014 and 2017, but this value does not exceed 35 in any of the experiments.

Graphic 6 - Final calibration best results for Subarea 3/2014 approaches



Source: Own Authorship

Graphic 7 - Final calibration best results for Subarea 3/2017 approaches



Source: Own Authorship

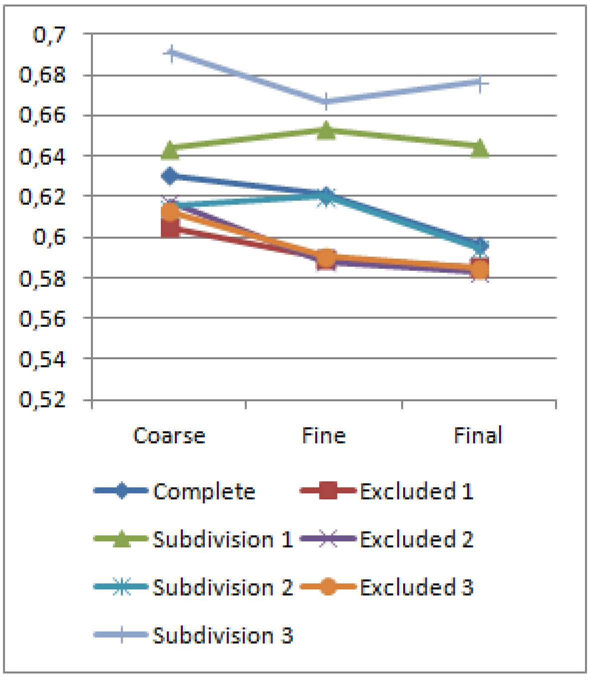
In the subdivision simulation there are significative differences in the Slope coefficient, for the approaches used for 2014. Slope resistance had moderate importance in this area, higher than in the simulation of the whole map and in the exclusion area approach. But the value of this coefficient decreases for 2017, which may represent that the new areas in the subdivision are not influenced by the slope. The RG coefficient also showed large variations in the best results of the Final calibration, both in 2014 and 2017 experiments.

6.2 METRICS

6.2.1 Lee Salee

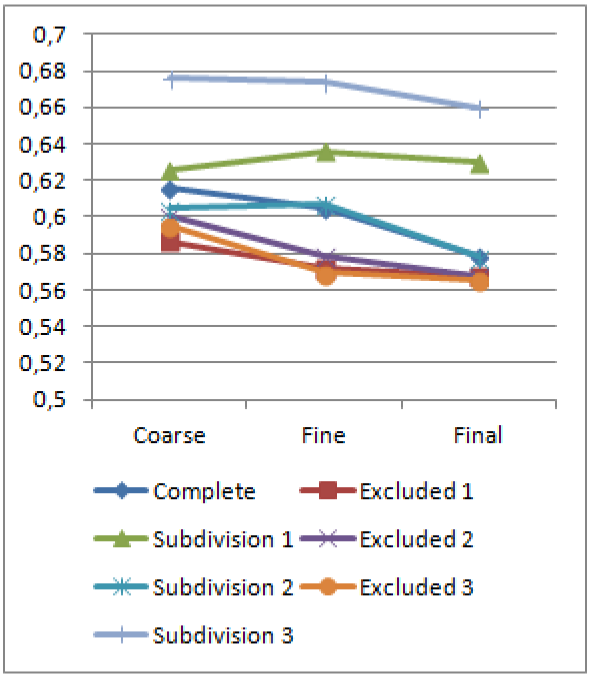
The definition of the top results in each calibration phase and selection of coefficients for the next step was based on the LeeSaale metric. It measures the spatial adjustment between the simulated city and the actual maps (OGUZ, 2004); the resulting values are between 0 and 1, which represents the perfect fit. Values of this metric are shown in Graphics 8 and 9, from the 2014 and 2017 simulations.

Graphic 8 - LeeSalee metric of 2014



Source: Own Authorship

Graphic 9 - LeeSalee metric of 2017



Source: Own Authorship

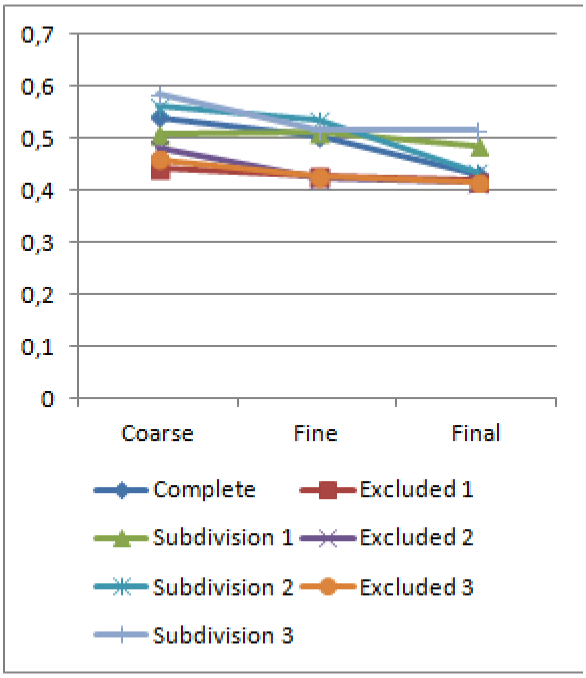
Analyzing this metric for the best scores of each simulation, it can be seen that the subdivision simulations had best results for S1 and S3. S3 showed 69% (0,69) of spatial accuracy in 2014, the best result of all the simulations executed. The remaining simulations had similar results in the coarse and final steps, distancing just in the fine phase.

The excluded areas approach had the lower results in both years. The probable cause is the fact that SLEUTH does not ignore excluded areas when it calculates statistics. This spatial accuracy for this type of simulation ranged between 55% and 69%.

6.2.2 Compare Metric

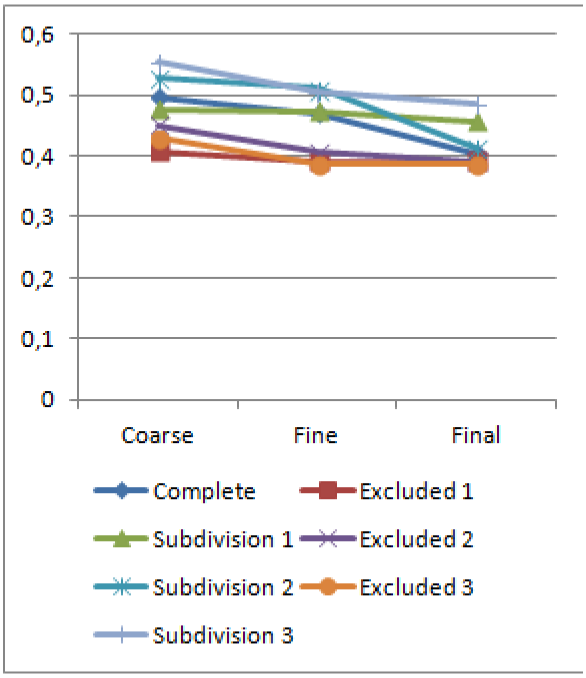
The ‘compare metric’ from SLEUTH makes a comparison between the amount of simulated pixels and the real ones (OGUZ, 2004), the results can range from 0 to 1. Results are shown in Graphics 10 and 11.

Graphic 10 - Compare metric of 2014



Source: Own Authorship

Graphic 11 - Compare metric of 2017



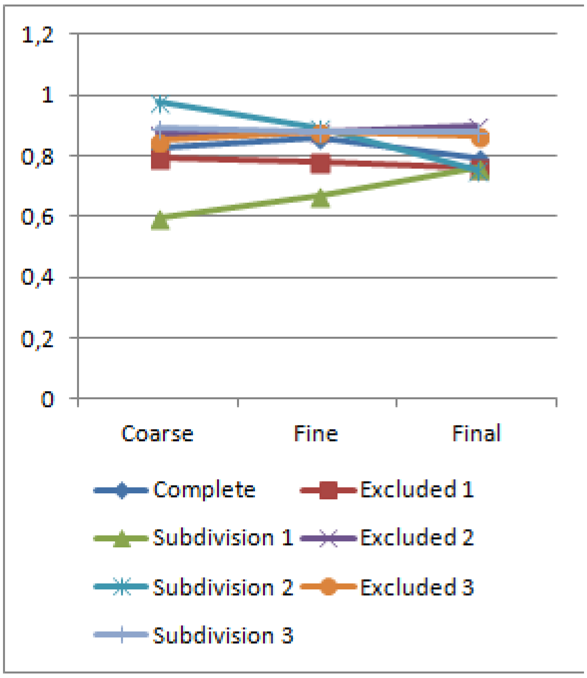
Source: Own Authorship

The results for this metric were mostly inconclusive, and varied between 38% (0,38) and 58% (0,58). Among all, by averaging the results of each phase, in both, 2014 and 2017, the best result was from S3.

6.2.3 Pop Metric

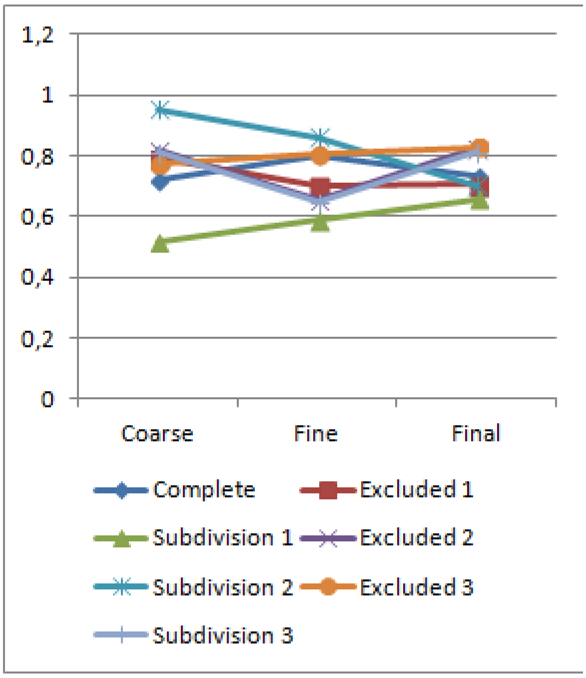
The ‘Pop metric’ employs Least Squares Regression to interpolate the number of urbanized pixels in the input maps (OGUZ, 2004), 0 is the lowest value and 1 the highest. The Graphics 12 and 13 illustrate this metric.

Graphic 12 - Pop metric of 2014



Source: Own Authorship

Graphic 13 - Pop metric of 2017



Source: Own Authorship

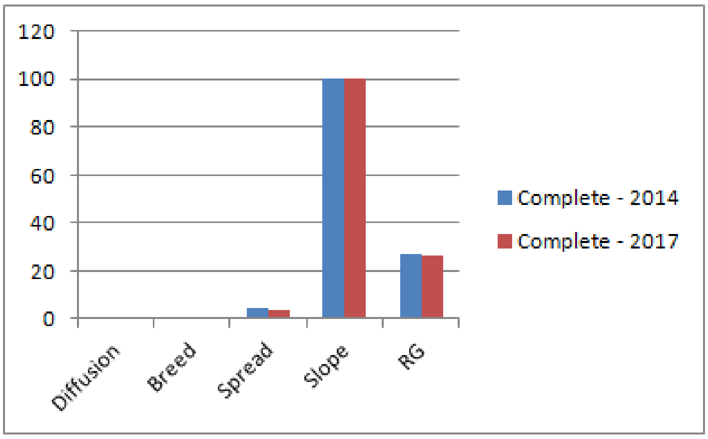
This metric, as in the previous one, showed mixed results. Almost all the results were not continuous or balanced. Between them, the best results were in 2014 were in S3 and E2, and in 2017 in S2.

6.3 FORECASTING AND PREDICTION RESULTS

Forecasts were calculated for the year 2017 and 2020 using the results from the calibration process, having as inputs images from 1984 until 2014 for 2017 and from 1984 until 2017 for 2020.

The values of forecasting parameters can be seen in Graphic 14. Of the five parameters, Spread showed unexpected low values, if compared to what was found in other experiments.

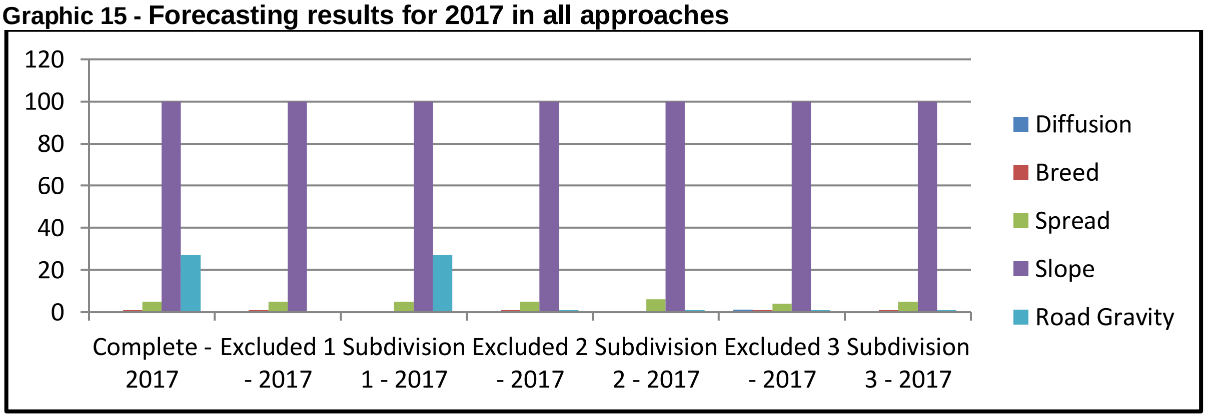
Graphic 14 - Coefficients derived from Forecasting



Source: Own Authorship

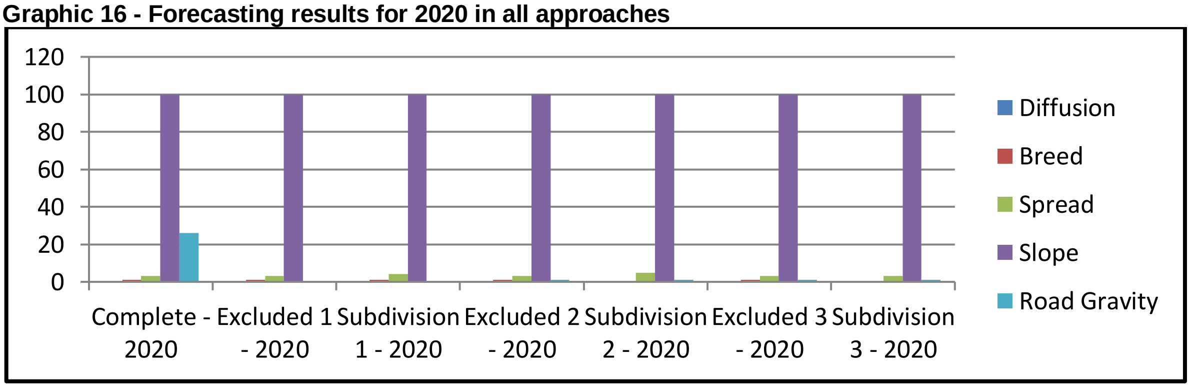
The same behavior happened in the rest of the simulations, as it can be seen in Graphics 15 and 16. After performing the Forecasting and Predict phases, it was possible to perceive that they were not in accordance with expectations. This because the resulting value for the Spread coefficient was very low, as well as the modeled pixels, and did not seem to agree with the behavior of the city, which is of continually growing.

Graphic 15 - Forecasting results for 2017 in all approaches



Source: Own Authorship

Graphic 16 - Forecasting results for 2020 in all approaches



Source: Own Authorship

6.3.1 Prediction for 2017

In this experiment, SLEUTH generated a low number of pixels, in all simulations performed. This is shown in Table 2. Approximately 47 pixels were documented in the avg.log in the simulation for the complete city, a total of 51 for the excluded areas approach and 55 for the subdivisions.

Beyond the modeled pixels documented in the logs, SLEUTH present in the resulting images pixels with different probabilities of creation. These pixels have different colors, which represent the probability of its appearance. A small tool was programmed to count pixels in the images. There were 842 for the complete simulation, 909 for the excluded areas and 992 to the subdivisions, all them had a low chance to appear, between 0 and 20%. These results were far from the actual map; the difference is about 9000 pixels, as shown in Table 2. The value of the sums of the excluded and subdivision are higher than the complete approach because of the overlap between neighborhoods, which is described in section 5.3.

Table 2 - Modeled Pixels vs. Real Pixels

	Avg.log	0 - 20% -SLEUTH	SLEUTH Total	Real Pixels
Complete	46,81	842	888,81	10223
Excluded 1	15,24	272	287,24	5429
Excluded 2	23,63	425	448,63	3554
Excluded 3	12,36	212	224,36	4100
Total	51,23	909	960,23	13083
Subdivision 1	15,04	271	286,04	5428,01
Subdivision 2	25,51	456	481,51	3554
Subdivision 3	14,5	265	279,5	4100
Total	55,05	992	1047,05	13083

Source: Based on SLEUTH outputs

The difference of growth rates between the SLEUTH simulation and the real data can be visualized in Table 3. It shows that the city had a considerable expansion in three years, which was not detected by the model.

Table 3 - Growth Rate - SLEUTH vs. Real

	SLEUTH	Real
Complete	0,618232396	6,995818791
Excluded 1	0,196564622	3,714506105
Excluded 2	0,307007459	2,432081024
Excluded 3	0,153534524	2,805043454
Subdivision 1	0,452251526	8,58210672
Subdivision 2	0,790994513	5,838288925
Subdivision 3	0,45510062	6,674282614

Source: Own Authorship

With a slight adaptation of the code that counted pixels, it was possible to verify the degree of coincidence between simulated and real pixels. The model also presented a low performance, as can be seen in Table 4, which shows that the hit rate was low, with a maximum of 35%.

Table 4 - Hits and Misses from SLEUTH results

	Misses	Hits	Total	% hits
Complete	559	283	842	33%
Excluded 1	210	62	272	23%
Excluded 2	276	149	425	35%
Excluded 3	138	74	212	35%
Total	624	285	909	31%
Subdivision 1	218	53	271	19%
Subdivision 2	326	130	456	28%
Subdivision 3	182	83	265	31%
Total	726	266	992	26%

Source: Own Authorship

Analyzing the avg.log derived from Forecasting phase, is possible to understand why the coefficients for the prediction were low. The Table 5 is derived from the avg log. It is possible to see that the model was not able to accompany the city development, showing a low number of urban pixels. The image for 2014 had approximately 146 thousand urban pixels, and SLEUTH calculated just around 63 thousand. Between 1987 and 1990 the city grew more than 10 thousand pixels, but the simulation generated only 129.

Table 5 - Information from the avg.log

year	index	area	grw_pix	real area
1987	1	61188.87	379.23	68471
1990	2	61983.88	219.56	79755
1993	3	62439.62	125.05	90453
		...		
2008	8	63027.33	11.07	123329
2011	9	63054.75	8.51	130485
2014	10	63075.23	6.22	146130

Source: Based in the complete approach simulation avg.log

6.3.2 Model Predictions for 2020

The prediction for 2020 repeated the behavior results of 2017. Table 6 shows the number of pixels generated in all the approaches used. For the complete map, SLEUTH modeled a total of 578 pixels for 2020. The excluded approach generated about 654 pixels in all approaches. The subdivision approach produced a total of 940 pixels for 2020. The results are shown in Table 6.

Table 6 - Pixels modeled by SLEUTH

	Avg.log	0 - 20%	Total
Complete	30,04	548	578,04
Excluded 1	11,86	195	206,86
Excluded 2	14,28	252	266,28
Excluded 3	9,96	171	180,96
Total	36,1	618	654,1
Subdivision 1	14,45	271	285,45
Subdivision 2	23,21	447	470,21
Subdivision 3	9,82	175	184,82
Total	47,48	893	940,48

Source: Own Authorship

According to these results, Ponta Grossa would grow about 0.60% in the S approach, 0.41% in the E and 0.36% in the complete simulation. These values are different than expected, as the city grew between 16.5% and 2.4% in the intervals used in the simulation. This can be seen in Table 7.

Table 7 - Urban layers information

Year	Urban Pixels	Urban %	Growth Pixels	Growth Rate %
1984	59822	2,69	-	-
1987	68471	3,13	8649	14,46
1990	79755	3,69	11284	16,48
1993	90453	4,43	10698	13,41
1996	100806	5,04	10353	11,45
1999	107895	5,53	7089	7,03
2002	112217	5,72	4322	4,01
2005	120469	6,14	8252	7,35
2008	123329	6,37	2860	2,37
2011	130485	6,76	7156	5,80
2014	146130	7,54	15645	11,99
2017	156353	8,19	10223	7,00

Source: Own Authorship

SLEUTH results were lower than expected in these simulations. More experiments were performed to see how the model would behave for 2030 using the same parameters used for 2020. The values obtained in these tests can be seen in Table 8.

Table 8 - Modeled pixels for 2030

2030	Avg.log	0 - 30%	Total
Complete	94,25	1627	1721,25
Excluded 1	37,42	622	659,42
Excluded 2	46,23	763	809,23
Excluded 3	30,66	521	551,66
Total	114,31	1906	2020,31
Subdivision 1	45,23	738	783,23
Subdivision 2	67,35	958	1025,35
Subdivision 3	30,56	526	556,56
Total	143,14	2222	2365,14

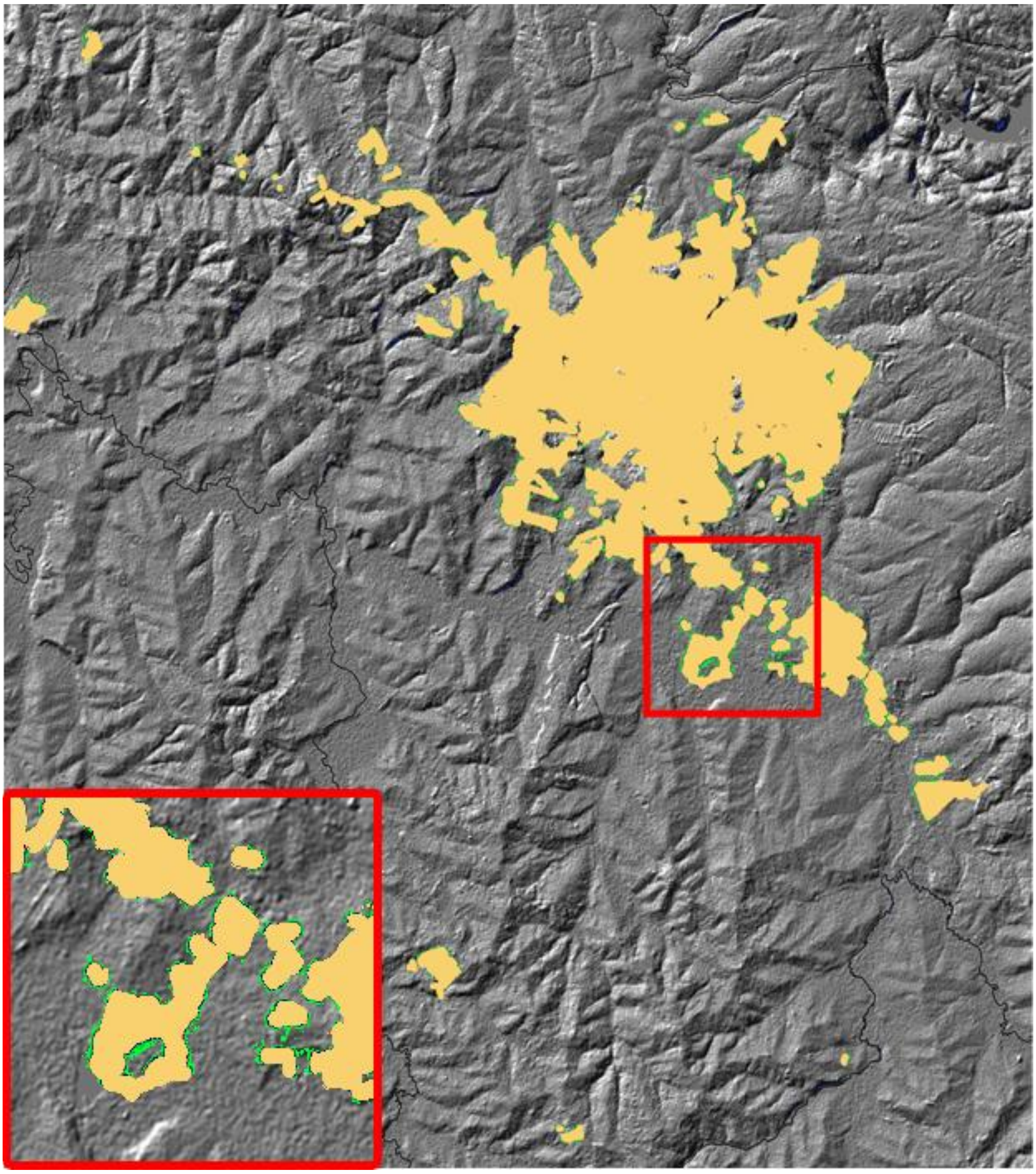
Source: Own Authorship

The number of pixels generated in the simulation was again lower than expected, and the sum of them was near the growth accumulated in three years according to Table 7. According to SLEUTH, Ponta Grossa would grow 1.1% in the complete simulation, 1.29% in E and 1.51% in S.

6.4 PREDICTION FOR 2020 AND 2030 - DIFFERENT PARAMETERS

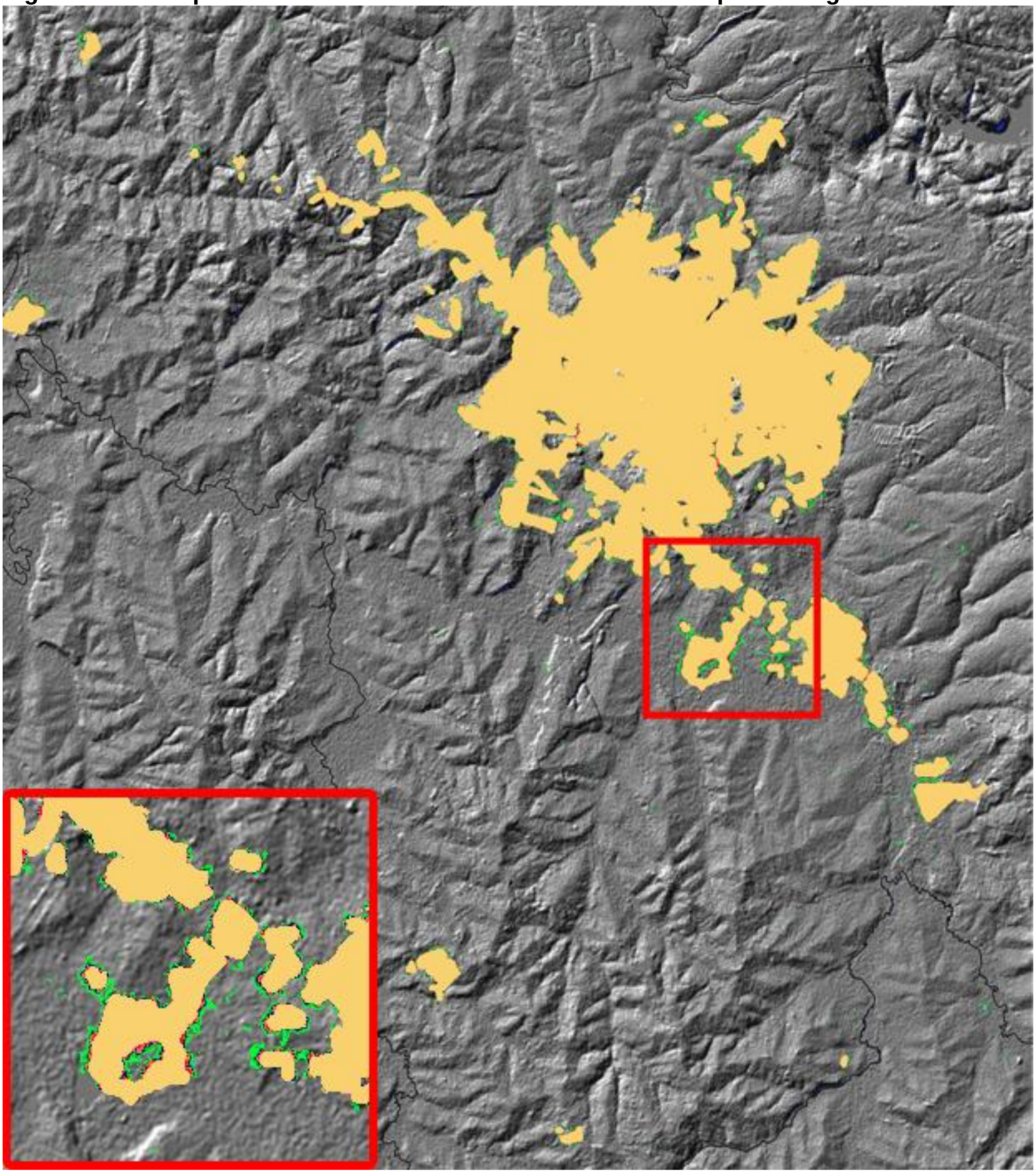
As the results obtained using the SLEUTH calibration values were different than expected, new settings were used to run predictions for 2020 and 2030. For this new experiment, it was used the complete simulation approach (with no regionalization of the maps). To define the parameters, it was observed the behavior of the results in the calibrations, and to seek higher growth percentage. The diffusion and breed were increased to enable random growth, the Spread was based in the final calibration results, and the Slope and Road Gravity were defined to have greater influence than seen in the calibrations. The parameters were set as following: Diffusion was set to 30, Breed 50, Spread 100, Slope 40 and RG 30. Figures 31 and 32 show the result for 2020 and 2030.

Figure 31 - 2020 prediction with zoom in one of the areas with probable growth



Source: SLEUTH

Figure 32 - 2030 prediction with zoom in one of the areas with probable growth



Source: SLEUTH

The results of both predictions had better results than the previous ones, and the city growth for 2020 was near to the usual city growth observed in the city maps. In this experiment, was also possible to observe others sets of growth probabilities, which can be seen in Table 9.

Table 9 - Pixels modeled for 2020 and 2030

Probabilities	2020	2030
0 - 10	2684	3813
10-20	1319	1425
20-30	1011	975
30-40	781	798
40-50	542	797
50-60	369	632
60-70	227	612
70-80	119	534
80-90	29	461
90-100	0	539
avg.log	1745,29	3689,39
Total	8826,29	14275,39

Source: Own Authorship

Using the parameters mentioned above, the results for 2020 were closer to the city usual growth. This result means that the calibration results for Ponta Grossa were inappropriate and the value for the Spread should be higher than the one achieved by SLEUTH. The results for 2030 were lower than expected, however they were better than the presented in the previous simulations.

6.5 ANALYSIS

Observing SLEUTH results it was possible to draw some conclusions about how the model responded to the data. SLEUTHs compute an average of the complete city behavior, what was expected, but if a region with complete different characteristics is part of the simulation some of them may be lost. When the subdivisions were simulated separately, SLEUTH results were slightly different for some coefficients, reveling different behaviors. One example is slope resistance, which, according to the results of the SLEUTH, has not the same importance across the city. There are also some differences in the Breed coefficient.

The type of growth in turn, proved to be highly organic in all the subdivisions. This was represented by the high Spread values, with very small differences among the simulations. Diffusion also presented a regular pattern, with low values for the all sub regions. Although the values were low, it was possible to observe that SLEUTH detected small changes in the Diffusion between 2014 and 2017, and this change of behavior can be observed in the maps used as input in the experiments.

Road Gravity results were irregular. The coefficient showed great variations in several simulations, and did not seem to have a big impact in the metric Lee Salle. In the simulations performed, this coefficient was significant only in a few cases. The relief of the city of Ponta Grossa is complicated; there is urbanization in very rough terrain, which may have influenced the unexpected behavior of the tool.

The Lee Salee metric, which is related with the spatial accuracy of the model, was above 0.5 and lower than 0.7. This might be considered an average result, but it was lower than expected. The Compare metric, which evaluates the amount of pixels modeled, had lower results than the Lee Salee, staying between 0.4 and 0.6.

In this work the LeeSalee metric was used in the calibration process, as indicated in the SLEUTH manual, but it is interesting to mention that the SLEUTH also has an alternative metric that can be used in the calibration process called the optimal SLEUTH metric (OSM). It was created by Dietzel and Clarke, 2007, and is based on several metrics of control_stats.log (population, edges, clusters, slope, x-mean, y-mean and compare) (HUA et al., 2014).

The simulations where only the excluded areas were altered produced some of the worse results. When the model simulates the city, excluded pixels are ignored and skipped. But, when the model calculates statistics and results, these pixels count normally, as can be seen in Chart 3, which presents parts of the SLEUTH algorithm.

Chart 3 - Spread and Leesalee algorithm

Spread code

```
static BOOLEAN spr_urbanize(int row, int col, GRID_P z, GRID_P delta,
GRID_P slp, GRID_P excld, SWGHT_TYPE * swght, PIXEL pixel_value, int
*stat){
   char func[] = "spr_urbanize";
   {...}
   if (excld[OFFSET ((row), (col))] < RANDOM_INT (100)){
      {...}
      stats_IncrementUrbanSuccess();
   }else{
      stats_IncrementEcludedFailure();
   }
   {...}
   }
```

Leesalee code

```
static void  stats_compute_leesalee (GRID_P Z, GRID_P urban, double
leesalee){
   {…}
   for (i = 0; i < mem_GetTotalPixels (); i++){
```

```
        if((Z[i] != 0)||(urban[i] != 0)){
           the_union++;
        }if((Z[i] != 0)&&(urban[i] != 0)){
           intersection++;
        }}
     *leesalee = (double)intersection/the_union;
     {…}
     }

```
Source: adapted from the SLEUTH algorithm

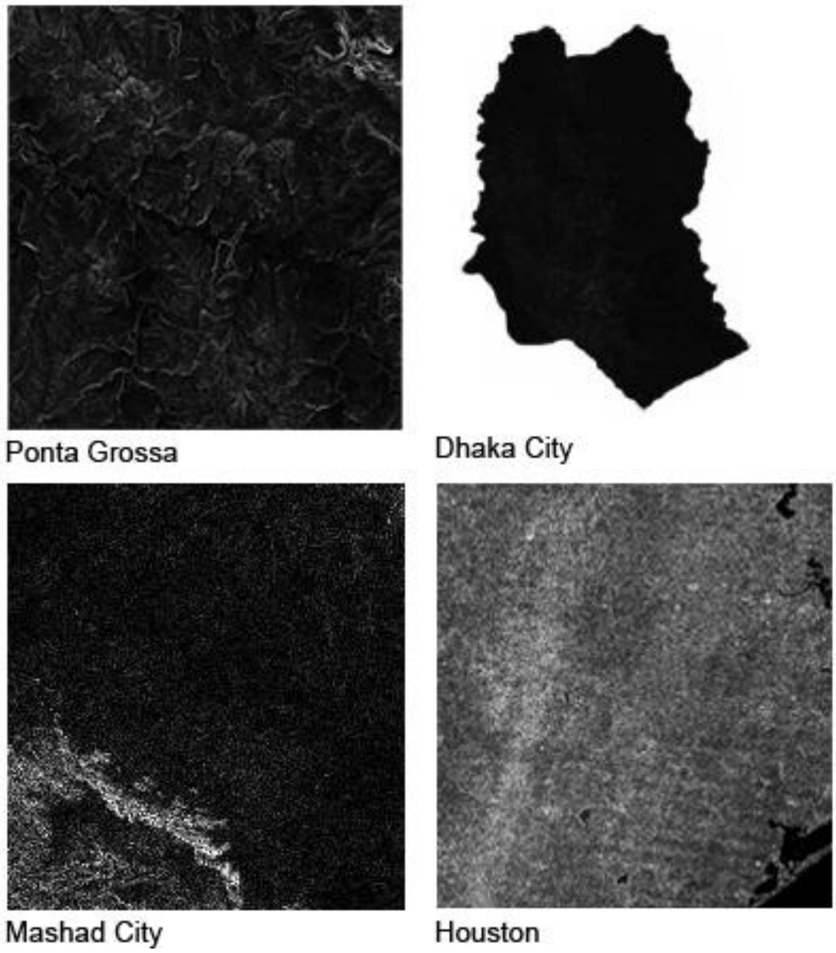
This behavior was not observed in the SLEUTH documentation, and in any text read during the survey.

Prediction values were very low in all simulations, and the number of generated urban pixels does not fit the reality. Ponta Grossa has very distinct characteristics of relief. A counter example, that would support this idea, would be the cities of:

- Dhaka City (PRAMANIK; STATHAKIS, 2016) which had Diffusion 1, Breed 36 , Spread 100, Slope 1 and RG 56; in this city it was used the OSM metric;
- Mashad City, with Diffusion 7, Breed 98, Spread 97, Slope 1 and Road Gravity 90 (RAFIEE et al., 2009) ;
- Houston (OGUZ, 2004) had a Diffusion of 1, Breed 3, Spread 100, Slope 22 and RG 17; it was used the LeeSalee metric to define the best results in the calibration process.

These cities were simulated in other studies, and the resulting coefficients were higher than those of Ponta Grossa, especially the Spread. In these cities simulation, the roads layer was less dense and the relief was significantly different. In Figure 33, the Slope layer from Ponta Grossa is being compared with the probable Slope used for these projects. Observing the images, is possible to see that Ponta Grossa Slope has more sudden changes of color, which means the slope is not regular and drastically changes in the area, while in the other images the slope is more regular, as some colors dominate the image.

Figure 33 - Ponta Grossa, Dhaka, Mashad and Houston relief



Source: Dhaka city (PRAMANIK; STATHAKIS, 2016); Ponta Grossa, Mashad and Houston were download from Earth Explorer and transformed using QGIS

Analyzing the log, it can be perceived that the self modification parameters were constantly used to reduce the spread coefficient, which resulted in very low values.

Observing Ponta Grossa city maps, it is possible to see that the city grows at least 2 thousand pixels each year, and SLEUTH results are not comparable with the reality. Observing the log, the model grew approximately 3 thousand pixels in 30 years, but in the input data is possible to see that the urban area grew about 80 thousand pixels. Besides this, the generated pixels had a low probability rate and are not being modeled in the right places as presented in chapter 6.

In an attempt to explain the results, some characteristics of the data can also be brought into question. The time interval used in this project was shorter than the majority of the experiments in the references. The urbanized portion of the images was small, corresponding to approximately 8% in 2017. The excluded part occupies almost 40% of the map. In the input files of the demo that comes along with SLEUTH to test the model, the urban layer of the last year available (1990), also have a small portion of pixels, about 10%, however the excluded areas embrace less than 11% of the map.

The urbanized regions of Ponta Grossa appear in disorganized patterns instead of a single mass. The road network used as input was denser than what was observed in other experiments, which were limited to highways. However, nothing in SLEUTH documentation indicates that the use of more detailed road information would lead to errors. Lastly, the Land Use layer was not used, although it is not a mandatory input, it could have helped in the calibration process and in the sensibility of the model.

After the execution of the simulations, it was possible to realize that the best kind of approach depends on the objective of the study. The subdivision approach is interesting to study a region that shows different, varying behaviors on historical maps. It must be noted that this is a time-consuming process. The calibration process, plus the prediction, extended for about 40 hours.

The usage of SLEUTH could be simplified or automated in some points. The calibration process could be automatic, since the setup of parameters follows simple rules based on tables of results. As SLEUTH uses the scenario file to assist in defining the model execution parameters for each calibration phase, this same file could be adapted so that the parameters of all calibration phases were informed at a single time. A sort feature could be added to the model, making it possible for all phases to be executed automatically, without intervention, saving time.

In Ponta Grossa city, it was possible to observe in the results some peculiarities, mainly in the subdivision approach, as the greater growth of subarea 2 in the predict phase. Among the approaches, the subdivision had better results in the metrics and number of modeled pixels. However, the prediction results in all approaches were very close, in all simulations, regardless of type used. Therefore, the time spent in the calibration is not justified by the model results. This kind of approach would be more interesting if less time was demanded, such as creating of a new exclusion layer, serving to define regions to be ignored both by the urbanization processes and statistics calculations.

7 CONCLUSION

Urban simulation is not a simple task. City processes include complex patterns and random behaviors that can be nearly chaotic. Simulating city aspects also involves qualitative information. The historical context can be important information to perform a simulation; the development of a characteristic over the years is essential to understand and to analyze the city behavior.

It is not difficult to understand why Cellular Automata models are widely used in urban simulation. It has the ability to create environments with complex patterns, being a clever choice to approximate city behavior. Besides that, they are quite simple to use and allow modifications to better fit the characteristics of the system being studied.

SLEUTH is a popular CA model used to simulate city growth. It is reasonably easy to use but requires historical data that may not be readily found. In this project the preparation of maps took a reasonable time, as the information was dispersed in several sources. In the present study, the city administration did not dispose of historical maps. Some images had to be prepared by hand, from satellite images. This is a time consuming procedure, which must be executed with care to avoid errors.

The regionalization of the city into regions was a matter of some debate, as there are infinite possibilities and no established rules to do that. In the present project it was created a subdivision based on the highways and streets, because it was not possible to find official regionalization which would satisfy the research needs. The regionalization needed to be consistent, and each of the area should have autonomy and capacity for growth and flow by itself. Between the characteristics pursued, it was necessary that each region had markets, pharmacies and banks. Also it was thought about the city culture, and how the population identifies some areas, and the best known neighborhoods for each region. In the process, some options were considered, as dividing the city in four pieces or by total area. But, the regionalization based on the streets and highways seemed the best choice, because by using this option the subareas had relatively good size and the necessary infrastructure. In addition, to preserve the features sought, the city center was added in all subareas to guarantee autonomy, and some areas are present in more than one subarea, to preserve the neighborhoods of the group.

The results obtained after performing the calibration phases, and executing the prediction, were different from what was expected. Until the final calibration process, the values of coefficients seemed to reflect the reality, matching the way the city grows. Road Gravity displayed, mostly, erratic values, but the analyzed city grows without a defined pattern, which may have been the reason for the model confusing results.

The metrics used had low to median values, never exceeding 70%. Analyzing the values in the avg.log, it is possible to observe that the simulated area is not comparable with the actual city growth.

Ponta Grossa is growing steadily, as can be observed in the input data, but the prediction coefficients derived from the forecasting were low in all the simulations performed. The model prediction for 2017 did not fit the way the city expands. The calculated growth was less than 10% of the real values and the modeled pixels were mostly in the wrong places.

Among the simulations, the results were all pretty close. Overall, the worst results were obtained with the Excluded approach. By comparing the results of all the simulation approaches, it seems that the complete simulation is the best choice. This because the subdivision approach had better results, but the time consumed was too long. While overall results did not correspond to the volume of expansion of the city, the experiments using different parameters showed that the model would be able to follow the grow patterns shown in historical data.

SLEUTH was able to simulate some characteristics of Ponta Grossa city, but not to attain quantitative results. This may have happened for several reasons.

It would be interesting to study the city land use, categorizing what a particular place was used for over time. This information could make possible to analyze how the transitions between rural and residential happen, the reaction of a region after the installation of a new industry, and how a new commercial spot impacts in the area where it is applied. These studies could analyze the attraction and repulsion forces, and track the development of commercial/residential areas. From this kind of information, could be possible to understand what makes the city grow more in one place than in another and analyze how the land use impacts on the city behavior and growth over time. For this study, CA models would also be a good choice, given the form they work.

Urban simulation and specifically the urban growth are tricky subjects. To be able to understand how they work it is necessary to study different aspects of a city separately, and merge them to see how they work together. The spatial spread, is only one of the elements that influence in how the city growth. This subject involves several other factors, as real state, land use transitions and industrial development. Thus, only studying spatial growth may not be sufficient for a model understand and define the patterns of a city. Therefore, in order to truly understand the growth pattern of the city, and obtain results closer to the reality, other studies contemplating the different aspects of urban growth must be carried out to be analyzed together with the spatial growth.

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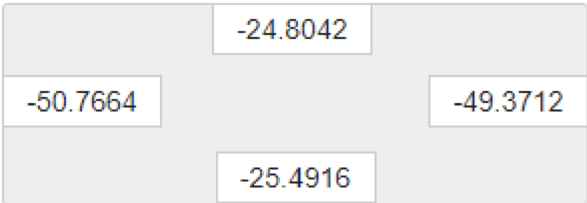
APPENDIX A - Layers Development

Layers development

ROADS

- After installing the OpenLayers plug-in, in the Quantum GIS software, go to the option Web > OpenLayers plug-in > OpenStreetMap > OpenStreetMap and inform the latitude and longitude data (Figure 35) to add the street map in the layers.

Figure 34 - Ponta Grossa latitude and longitude



Source: OpenStreetMap

- To add the administrative city borders, go to Layer > Add Layer > Add Vector Layer and choose the shape file downloaded from the IBGE site.
- After arranging the image with the necessary size, using the option File > Save Screen as Image, choose the .jpg option.
- Open the Photoshop.
- Create a new project and add the .jpg derived from QuantumGIS as a new layer.
- Select the white color using the option Select > Color Range and erase the selected parts.
- Create a new layer and paste in that the satellite image from 2014 and spatially fit the layers as Figure 35.

Figure 35 - Roads vector over the satellite images

Source: Adapted from Google Earth and OpenStreetMap

- Create a new layer, and draw the missing streets using the Line Tool.
- Select all shapes created, click with the right mouse button and select the option Group into a New Smart Object.
- Select the new object and use the mouse right button to choose the option Rasterize Layer.
- Selecting both roads layers, click with the right mouse button and select the option Group into a New Smart Object.
- Click with the right mouse button in the new object and select the option Rasterize Layer.
- Erase the streets without connection and out of the city border.
- To have layers with different colors (given its importance) create a new layer.
- Overlap the roads vector with this layer, and using the Line Tool draw the streets of interest.
- Group all the shapes created by the line tool selecting then and using the option Group into a New Smart Object.
- Select the new object and use the option Rasterize Layer.
- Paint the streets with the respective shade.
- Select the created roads layers, and using the mouse right button chose the Group into a New Smart Object option.
- Click in the object with the mouse right button and chose Rasterize Layer.
- To create the historical layers duplicate the roads layers from 2014.

- Add a new layer, and paste the satellite images from the historical year behind the roads layers.
- Using the Eraser Tool, erase the streets that are not in the satellite image.
- Create a new layer, and paint it in black, put it behind the roads layer.
- Save the project.
- Keep just the black layer and the roads for the year being saved, hide the others.
- Transform the image color using the menu Image > Mode > Grayscale (it may keep just one layer and erase the others).
- Save the image as .gif.
- Choose the option Edit > Redo Grayscale.
- Repeat the process to save the other layers.

URBAN

- After downloading the images from the selected source (Google Earth and INPE), open the Photoshop.
- Create a new layer for each satellite image available for the years being developed and paste the satellite images (Figure 36).

Figure 36 - Satellite Layers

Source: Adapted from Google Earth and INPE

- Fit the images spatially when necessary.

- For assistance, create new layers for the previous and subsequent years and paste the satellite images.
- Create a new layer over the satellite images.
- Zoom in on the images.
- Detect the urban areas and color then using the Brush Tool in the empty layer.
- When reach to areas that are difficult to identify, use the previous and subsequent year's layers.
- Repeat the process for all the needed years using a different color for each one.
- Starting in the first year develop, using the layers overlap, verify the borders of each spot.
- Paint the spots of all the years in white.
- Create a new layer, and paint it in black, put the layer behind the urban layers.
- Save the project.
- Keep just the black layer and the urban spots for the year being saved, hide the others.
- Transform the image color using the menu Image > Mode > Grayscale (it may keep just one layer and erase the others).
- Save the image as .gif.
- Choose the option Edit > Redo Grayscale.
- Repeat the process to save the other layers

EXCLUDED AREAS

- After downloading the Conservation Unit section from the Director Plan, open Photoshop.
- Create a new layer, and paste a satellite image for any year.
- Create a new layer and paste the conservation unit image.
- Fit the images spatially, using transparency in the conservation unit image (Figure 37).

Figure 37 - Conservation Unit image over satellite image

Source: Adapted from Google Earth and IPLAN

- Create a new layer.
- Crop the conservation areas from the conservation unit image.
- Paste in the new layer.
- Paint the pasted area in white.
- Select the area outside the city borders.
- Create a new layer.
- Crop the area.
- Paste in the new layer.
- Paint the pasted area in white.
- Create a new layer, and paint it in black, put the layer behind the created layers.
- Save the project.
- Keep just the black layer and both created layers visible, hide the others.
- Transform the image color using the menu Image > Mode > Grayscale (it may keep just one layer and erase the others).
- Save the image as .gif.

SLOPE AND HILLSHADE

- After downloading four tiff images from Earth Explorer, open the Quantum GIS.
- Create a new project.
- Add the images.
- Correct the scale by 11120 in the Scale ratio vertical units to horizontal box as is advised in the Quantum GIS manual.
- Add the IBGE administrative borders shapefile.

- Go to Raster > Analysis > DEM (Terrain models).
- Select the Hillshade option.
- Click in OK.
- After arranging the image with the necessary size, using the option File > Save Screen as Image, choose the .jpg option.
- Go to Raster > Analysis > DEM (Terrain models).
- Select the Slope option.
- Choose the Percentage option.
- Click in OK.
- After arranging the image with the necessary size, using the option File > Save Screen as Image, choose the .jpg option.
- Open the Photohosp
- Create two new layers and paste the images for the Slope and Hillshade
- Create a new layer and paste a satellite image.
- Spatially fit the layers in the satellite image using the layer transparency (Figure 38).

Figure 38 - Slope over satellite image

Source: Adapted from Google Earth and Earth Explorer

- Save the project.
- Keep just the Slope layer visible, hide the others.
- Transform the image color using the menu Image > Mode > Grayscale (it may keep just one layer and erase the others).
- Save the image as .gif.
- Choose the option Edit > Redo Grayscale.
- Repeat the process to save the Hillshade.