Application of SLEUTH model to predict urbanization along the Emilia-Romagna coast (Italy): considerations and lessons learned

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Abstract. Coastal zone of Emilia-Romagna region, Italy, has been significantly urbanized during the last decades, as a result of a tourism development. This was the main motivation to estimate future trajectories of urban growth in the area. Cellular automata (CA)-based SLEUTH model was applied for this purpose, by using quality geographical dataset combined with relevant information on environmental management policy. Three different scenarios of urban growth were employed: sprawled growth scenario, compact growth scenario and a scenario with business-as-usual pattern of development. The results showed the maximum increase in urbanization in the area would occur if urban areas continue to grow according to compact growth scenario, while minimum was observed in case of more sprawled-like type of growth. This research goes beyond the domain of the study site, providing future users of SLEUTH detailed discussion on considerations that need to be taken into account in its application.

Keywords: SLEUTH · Urban Growth · Land Use Planning · Cellular Automata · Scenarios

1 Introduction

Uncontrolled urbanization can lead to series of environmental issues, such as encroachment of natural habitat and agricultural land, high energy or water consumption and waste generation, among others [1]. Worldwide, urban growth is particularly taking part in coastal areas [2]. For instance, between 1990 and 2000 the urbanization rates of European coastal regions were approximately 30% higher than in inland areas [3]. One of the hotspots of urbanization in Europe is the coastal zone of Mediterranean region, where urban growth is driven to large extent by tourism development [4]. A relevant example is the coastal zone included within the administrative boundaries of Emilia-Romagna region, Italy. It was heavily urbanized in decades following the Second World War, mainly due to the development of beach related tourism [5]. Since this area is characterized by low lying setting and sandy beaches, it is susceptible to inundation and erosion, caused mainly by marine flooding [6].

In order to study Emilia Romagna's vulnerability to coastal flooding in dynamic manner, a previous study [7] compared flooding scenarios with outputs of different scenarios of urban growth. For marine flooding scenarios this was done by applying functions implemented in the Cost-Distance tool of ArcGIS® to a high resolution Digital Terrain Model [8]. The urban growth scenarios were estimated by applying the SLEUTH model [9]. SLEUTH belongs to the group of cellular automata (CA) models, known for the ability to capture complex non-linear behaviour in growth patterns and self-organization emerging from the local interaction between cells and their neighbours.

This study faces issues related to the use of the SLEUTH model to project urban growth on regional level by using geographical dataset at high spatial resolution and all available information related to the environmental management policy. This includes a detailed step-by step discussion on SLEUTH application throughout all of its phases, highlighting some potential considerations and summarizing the lessons learned. The output of this paper could serve all researches that consider the application of SLEUTH to introduce the best practice in the field of present and future environmental management and planning.

2 SLEUTH Model

SLEUTH is a self-modifying probabilistic cellular automata model. It is a public domain C-language source code that runs under UNIX or UNIX-based operating systems, structured into two modules that can be activated independently. One module is the Urban Growth Model (UGM) that simulates the urban growth, and the other is Land Cover Deltraton Model (LCD) that simulates the changes in land use. The code is publicly available on Project Gigalopolis website [10], a project born from collaboration between the University of California of Santa Barbara (UCSB) and United States Geological Survey (USGS).

SLEUTH's acronym is derived from its input requirements: Slope, Land use, Exclusion, Urban, Transportation and Hillshade. In brief, it can be described as a scale-independent CA model with Boolean logic, since each cell can be categorized only as urbanized or non-urbanized. Whether or not a cell becomes urbanized is defined by four transition rules of urban growth: spontaneous, diffusive (new spreading centre), edge growth and road-influenced growth. These rules are controlled by five coefficients with values ranging from 0 to 100: dispersion (DI), breed (BR), spread (SP), road gravity (RG) and slope resistance (SR) coefficient [11]. Relationship between the growth types and growth coefficients is schematized in Figure 1.

Growth coefficients do not necessarily remain static throughout the model application. If growth rate exceeds or falls short of limit values, a self-modification process is applied. Without this feature, the growth could appear as linear or exponential, which is unrealistic [12, 13].

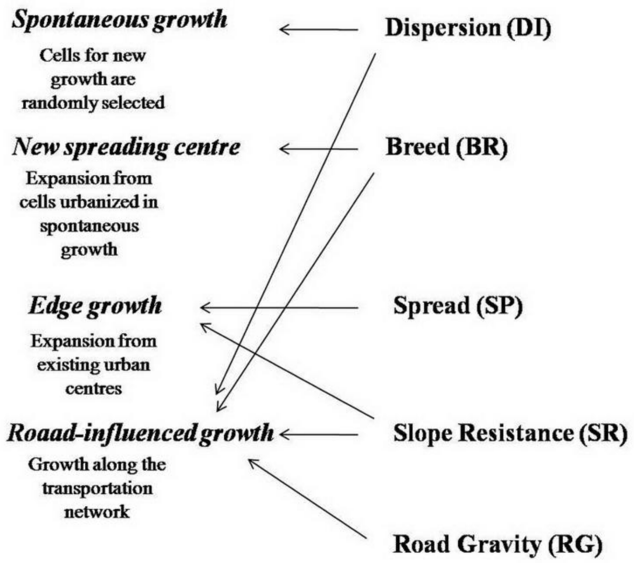

Fig. 1. Relationship between growth types and growth coefficients in SLEUTH (adapted from [14] and [15]

The model is implemented in two general phases: calibration phase, which simulates historic growth; and prediction phase; which uses patterns of historic growth to derive scenarios for future growth. The output of the model is a series of GIF images showing the predicted urban growth scenarios for each year.

All details on SLEUTH phases and other considerations (e.g. input data), are explained in the following section, through an example of our application of the model on the coastal area of Emilia-Romagna region.

3 Application of SLEUTH on the Coastal Area of Emilia-Romagna (IT)

This section describes the overall methodology related to: (i) selection, quality and overall characteristics of input data; (ii) calibration process; and (iii) design of three scenarios used for prediction.

3.1 Input Data

SLEUTH requires five types (or six, if land use is included) of input data: historic urban cover of at least four time periods, historic transportation network of at least two periods, slope, hillshade, and exclusion layers. All raster or vector-based layers in the end need to be attributed to a reference grid and successively converted into GIF images of same number of rows and columns.

In our case all input layers were prepared in SAGA (System for Automated Geoscientific Analyses) and ArcGIS 10.1 software. They were clipped to the same extent (rectangle of approximately 76 km of length and 26 km), representing a portion of the coastal zone of Emilia Romagna.

Urban layers were digitized for the years 1978, 1990, 2000 and 2011, from different sources. The 1978 urban layer was derived from 1:5000 scale topographic map provided by the Regione Emilia Romagna. The 1990 urban layer resulted from the digitizing of a LANDSAT image at 30mx30m spatial resolution, obtained from the United States Geological Survey (USGS) Global Visualization Viewer (GloVis) web service (http://glovis.usgs.gov). The 2000 urban layer was based on the aerial photogrammetric surveys after the 1999-2000 Istituto Geografico Militare Italiano (IGMI) flight (1:29000 scale, 0.65 m spatial resolution). Finally, for the year 2011 urban areas were digitized by using the World Imagery Basemap feature in ArcGIS 10.1, with high resolution (0.3 m) imagery of Western Europe provided by Digital Globe®.

Two transportation layers were prepared for years 1978 (the same topographic map as for 1978 urban layer), and for 2011 layer (from Web Mapping Service of Italian National Geo-portal: www.pcn.minambiente.it). Both layers took into consideration provincial and national level of roads, as well as highways.

Regarding Slope and Hillshade layers, they were both created from a 10mx10m Digital Terrain Model (DTM) provided by Regione Emilia Romagna after being resampled to a 20 m resolution by using the nearest neighbour method. As required by the model, the slope was extracted in percentage values.

Special attention was given to the Exclusion layer. Two different exclusion layers were considered: the first one referring to historical settings, used for calibration purposes; and the second one, used for the prediction stage. The need for such an approach deserves further explaining. Calibrating the model with current exclusion layer could be erroneous since many areas have received their protection status in period between the first historical year of calibration and the most recent one [16]. Early periods of calibration would therefore get informed by the actual distribution of currently excluded areas, leading to better fit in calibration in sort of “manipulative” manner [15].

Both of our exclusion layers had joint exclusion areas which remained unchanged, such as the sea and inland water bodies. The present exclusion layer contains additional zones where construction is prohibited, such as different zones of protected natural areas on a regional level; national reserves; sites of community importance related to the Natura 2000 network of the EU Habitats Directive (92/43/EEC); zones of special protection related to the EU Birds Directive (79/403/EEC), different protection levels of archaeological sites; and 150 m buffer zones around river banks and 300 m buffer around shorelines (see [7] for more details). Historic exclusion layer included only areas which were known as areas with prohibited construction since the very beginning of the time period used for calibration.

All input layers were converted into 20 m resolution raster grids of 1323 columns by 3816 rows using SAGA software and saved as greyscale GIF images, as required for the calibration stage.

Input layers are shown in Figure 2.

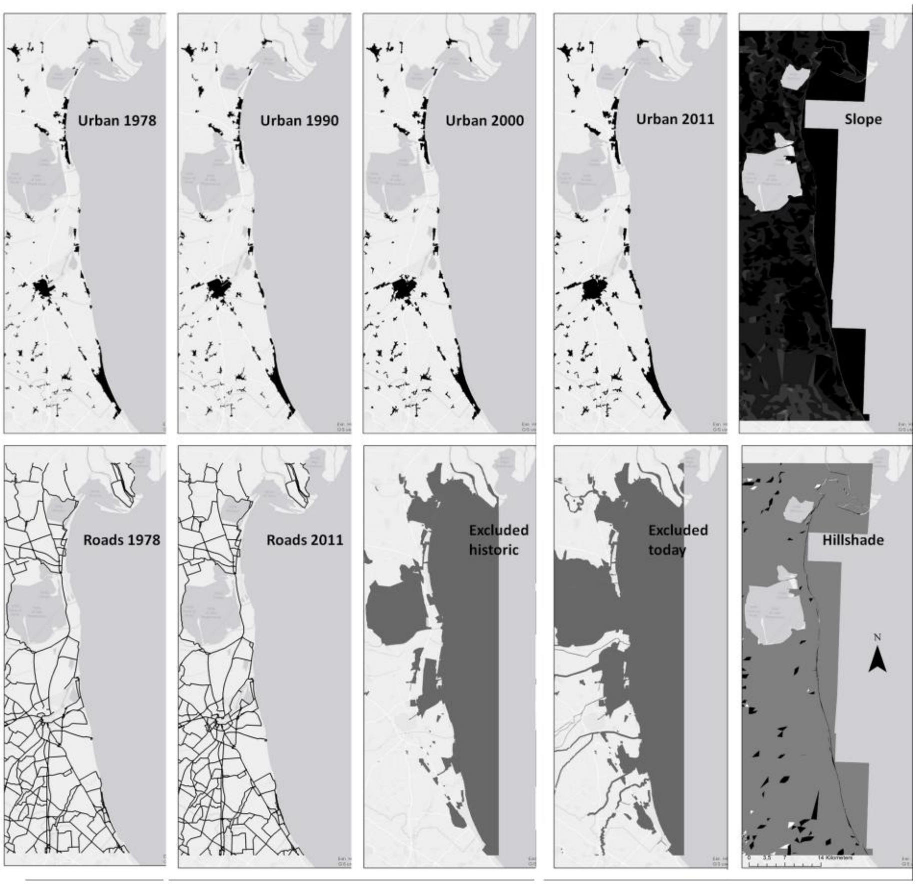

Fig. 2. All input layers for SLEUTH model

3.2 Model Calibration

The main goal of the calibration phase is to determine the values of growth coefficients that simulate urban growth for certain historic time periods. SLEUTH calibration is carried out through a "brute force" method which consists of three phases: coarse, fine and final [17]. Growth is simulated multiple times by using the Monte

Carlo method, an iterative procedure used for computation of different spatial statistics [18-19].

In the coarse calibration phase, the widest range (1-100) of coefficient values is used, incremented of 25 at a time. The range of coefficients values used in calibration's subsequent phases (fine and final) is narrowed based on coefficient values that best replicate the historical growth in each preceding phase.

Self-modification constraints are causing coefficient values to be constantly altered from the first date to the last date of the run. For that reason, the best coefficient set for forecasting is actually derived by averaging the resulting values coming out from the final phase. In our case, this was done through 100 Monte Carlo simulations (with 1 step increment) so that an average value for each coefficient could be derived (read more in [14]). We named this additional phase "derive", according to [15]. This procedure is also recommended in the official website of the Gigalopolis Project.

In order to obtain the coefficient range of each successive step of calibration, we used the goodness-of-fit metric called Optimal SLEUTH Metric (OSM). The OSM is a product of the most relevant metrics offered by the code - compare, population, edges, clusters, slope, X-mean, an Y-mean metrics [20][16].

The resulting values of the calibration parameters for our study site, concerning all calibration phases, are visualized in Table 1. The coefficient range for successive steps of calibration was selected by examining the top three rankings of the OSM values, as indicated on the official Project Gigalopolis website. The highest OSM value increased with each calibration step (from 0.38 in coarse to 0.397 in final phase), meaning that the resemblance between modelled and observed data improved as calibration progressed.

Table 1. SLEUTH calibration parameters for 1978-2011 historic urban growth of Emilia-Romagna coastal area (from [7])

	COARSE		**FINE**		**FINAL**			**DERIVE**		
	Monte Carlo iterations = 4		Monte Carlo iterations = 7		Monte Carlo iterations = 9			Monte Carlo iterations = 100		
Growth coefficients	Range	Step	Range	Step	Range	Step	Final	Range	Step	Final
DI	1-100	25	0-20	5	0-5	1	1	1-1	1	1
BR	1-100	25	0-20	5	0-5	1	1	1-1	1	1
SP	1-100	25	15-35	5	20-30	2	24	24-24	1	30
SR	1-100	25	0-75	10	0-10	2	10	10-10	1	1
RG	1-100	25	0-50	10	10-50	5	50	50-50	1	52

The low final values of the DI (1) and the BR (1) coefficients imply that there was very little sprawled growth in the coastal area of Emilia Romagna for the 1978-2011 period. The value of the SP coefficient (30) indicates that growth occurred in a more compact manner, around existing urban areas. High value of the RG coefficient (52) implies that the road network played an important role in attracting urban development. Low value of the SR coefficient (1) was somewhat expected, since the study area is characterized by an extremely low slope variations and, therefore, slope does not represent a limiting factor for growth. It appears that self-modification parameters did influence the coefficient values that came out of the final phase, since they changed towards derive phase for SP, RG and especially for the SR coefficient.

3.3 Model Prediction – Development of Urban Growth Scenarios to the year 2050

There are three different approaches to develop scenarios of urban growth within SLEUTH: (i) changing the values of growth parameters obtained through the calibration phase (e.g. [21][14]), (ii) assigning different protection levels to the exclusion layer (e.g. [22, 23]), and (iii) manipulating the self-modification constraints (e.g. [24]).

In our study, we used the combination of the first two approaches: both growth coefficients and exclusion levels were modified to establish different scenarios of urban growth up to 2050. Three growth scenarios were designed - the Business As Usual

(BAU) scenario, which assumes that future urban development will follow the same pattern as in history, and two "alternative" scenarios: the Sprawled Growth Scenario (SGS) and the Compact Growth Scenario (CGS). The characteristics of all three scenarios are summarized in Table 2.

Table 2. Scenarios used for SLEUTH prediction

Scenario	Main characteristics	Impacts on values
Business As Usual (BAU)	The parameter values are the same as ones resulted from calibration were used	
Sprawled Growth Scenario (SGS)	Dispersive growth: new sub-urban and peri-urban centres likely to emerge (mainly in existing agricultural and forested areas).	Higher values for DI and BR coefficients
	The "infilling" growth is expected to be minimal	Reduced value of the SP coefficient
	Higher probability for growth along the road network since sprawled growth could result in greater travel distances	Higher value for RG
	Spatial planning is more aimed at satisfying high demand for urban areas	Flexible exclusion levels
Compact Growth Scenario (CGS)	Compact-like growth	The DI and BR values were lowered while SP was increased
	Reduced travel distances	Lower RG value
	Less demand for urbanization outside already urbanized areas and hence, less rationale to allow construction in areas that are currently protected	Maximum exclusion levels assigned

Prior to decision making which exact value to assign to different growth coefficients to fit different scenarios, a sensitivity analysis was performed. This was done in order to examine how each single coefficient affects urban growth in our case. The prediction (100 runs) was executed by assigning high value (80) to each coefficient while keeping the values of other coefficients as low as possible (1) (similar to [13]). The results revealed that the SP coefficient had by far the highest impact on urban growth (increase of urban cover by 11.25%), while DI, BR and RG coefficients proved to be less significant in influencing the increase of urban cover (0.35%, 0.14% and 0.11% respectively). Keeping in mind the results from this sensitivity analysis, the coefficient values for two alternative scenarios were established in following manner:

- In SGS scenario the values of DI, BR and RG were increased by 25, while SP coefficient was decreased by 10 ("only" by 10, because of high affinity of urban increase to changes in SP values shown in sensitivity analysis). Exclusion levels were arbitrarily weighted with a value of 80, meaning that there is an 80% probability that the exclusion level will remain as such in areas where urban development can be permitted under certain conditions.
- In CGS scenario the DI and BR remained at minimal values while RG was decreased by 25. The SP was decreased by 10. Maximum exclusion levels were assigned to all polygons within the Exclusion layer (100).
- The SR coefficient was not modified in any of the alternative scenarios since it was shown not to be a limiting factor for the urbanization in the area
- The BAU scenario remained with the same values of growth coefficients that resulted from the calibration. Exclusion levels were weighted with a value of 80 for the same reason as in SGS

Finally the values for the "alternative" scenarios were: for SGS: DI (25), BR (25), SP (10), SR (1), and RG (77); and for CGS: DI (1), BR (1), SP (40), SR (1), and RG (27). With established coefficient values for all scenarios, the prediction was executed by running 100 Monte Carlo iterations. The results for urbanization up to 2050 were the following: the SGS predicted minimum increase in urbanized areas: 0.76 %. On the contrary, the maximum increase in urbanization was predicted by the CGS: 7.26%. The BAU predicted an increase of urbanized areas by 3.7%. More details on results are shown in Table 3. It seems that a transition from compact to sprawled type of urban growth is not likely to occur in the study area according to SLEUTH predictions for the future. In other words, if urbanization continues to take place in the area, it will most probably happen around the existing urban areas, in compact manner. Prediction for 2050 is illustrated in Figure 3 for all three scenarios. The figure depicts only a portion of the study area for visualization reasons.

It seems that more compact urban development in the past made a mark on the prediction for the study area. This is particularly evident in the example of SGS scenario. Although some sparse urbanized areas appear in this scenario, their probability of occurrence is less than 20%. The fact that the SGS showed the lowest to-urban conversion even though the DI and BR values were increased by 25, implies how dominant was the SP coefficient in the control of urbanization, even though it was changed by a lower value. Moreover, it could be that the sprawl was hindered by great share of Exclusion in the area (see Figure 2). All in all, the results indicate that urbanization levels until 2050 will be relatively low in the area. This could be related to the fact mention above – considerable share of area that is either urbanized or excluded from development. In addition, the scenarios were driven by the information coming from calibration, which in our case, initiated with 1978, i.e. after the period in which the biggest boom of urbanization took place (1950s and 1960s [5]). The quality data for the pre-1978 period were not available to "capture" this "boom" in the calibration.

Table 3. Share of the number of urban pixels in the total number of pixels (%urban) and the percent of the new urban pixels in one year divided by the total number of urban pixels (grw_rate) for all three scenarios up to 2050

	BAU		SGS		CGS	
Year	%Urban	Grw_rate	%Urban	Grw_rate	%Urban	Grw_rate
2012	10.29	1.06	10.27	0.88	12.07	1.36
2020	11.05	1.17	10.67	0.42	13.31	1.63
2030	12.11	1.11	10.89	0.19	15.14	1.53
2040	13.19	0.99	10.99	0.09	17.13	1.44
2050	13.99	0.44	11.03	0.05	19.33	1.39

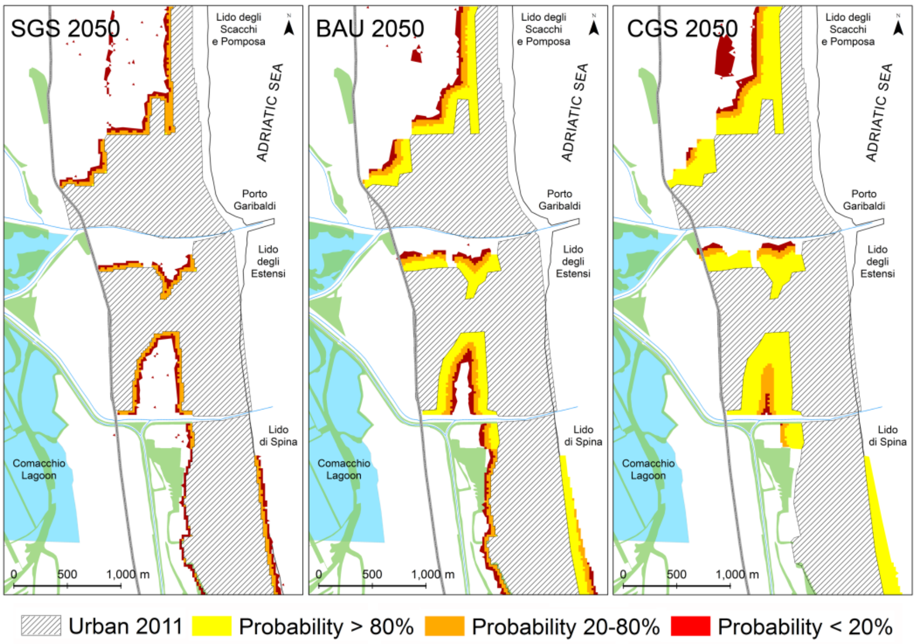

Fig. 3. Probability of urban growth for 2050 for part of the Emilia-Romagna coastal region according to CGS, BAU and SGS scenario

4 Discussion and Conclusions

Like any other model, SLEUTH has its own limitations, as well as uncertainties that can emerge during its application. Like many urban models, it cannot capture the driving forces behind urban growth [12]. Which factors will drive urbanization in the future, and to what extent, is dependent on complex interrelationship between uncertain future demographics and socio-economic aspects [25]. However, it seems that SLEUTH is deliberately focused more on form and dynamics, i.e. “where” could the development take place, not “why” [26]. In addition, SLEUTH is sensitive to time resolution and spacing, geographical resolution and scale, and the classification scheme applied to land use. It is neither capable to capture the interior structure of cities, nor to create destiny estimates within them. Finally, there is no explicit model of uncertainty in SLEUTH, although it is accounted for [26].

Some uncertainties were also encountered in our study, during different steps of SLEUTH application. Initial concern was the appropriateness of input data. All of the available maps for historic urban extent were from different sources, with different spatial resolution. This can be of particular significance since SLEUTH performance can be sensitive to different sources of input data, even when they cover the same geographical area [27]. On the other hand, the input datasets used were relatively recent with no big gaps between time series. This is highly important since SLEUTH seems to show temporal sensitivity regarding historic datasets. Using more dense historic observation points, i.e. shorter time series, may produce better agreement between the simulated and observed urban growth [18].

One of main uncertainties regarding calibration was the choice of goodness-of-fit metric that implies the most relevant coefficient values for each successive phase. Although many earlier applications of SLEUTH used some other metrics (Lee-Sallee metric in particular), we employed the OSM since it is believed to be the most robust measurement of model accuracy with the past data [20]. However, since OSM is a product of several values ranging from 0 to 1, even small differences from 1.0 can quickly compound downward. It is important to remember that the values of component metrics of OSM are not in correlation in rankings, i.e. the highest OSM value does not correspond with the highest of any of its constituent metrics [16].

In this study we did not alter the resolution of the input images throughout the different phases of the calibration process. Lowering the resolution of input images is a common practice to reduce computation intensiveness [28]. However, changing the resolution of input layers may influence the growth rules, impact the overall performance of the model and finally, lead to inaccurate representation of growth [29]. By taking these observations into consideration, the resolution of input images was kept the same (20m cell size using the nearest neighbor resampling algorithm) throughout the whole calibration process.

Other concerns were mainly related to the design of the scenarios. There are numerous issues that need to be taken into consideration when developing scenarios of land use change [30]. We opposed the two alternative scenarios sprawled vs. compact type of growth, a concept that was also used, in similar manner, in some earlier applications (e.g. [21] [31, 32]).

One uncertainty related to the scenarios was how much to increase/decrease the coefficient values in order to represent scenarios. We have performed a sensitivity analysis, based to some extent on [13], to help us in making such a decision. However, it needs to be said that this kind of sensitivity analysis perhaps oversimplifies the connection between single coefficient and certain type of growth. In other words, all growth coefficients are highly correlated to each other and certain type of growth is a product of their interaction. Different coefficients do not necessarily need to be inversely related within a scenario. For example, even if a scenario aims to reflect a sprawled growth (i.e. DI and BR coefficients increase) this does not mean that the compact growth should automatically decrease, and vice versa. Some studies used different methods to estimate whether an urban area is passing through a sprawl phase or a coalescence phase during certain time period. These include calculating a ratio between the number of clusters and average cluster size [33] or computing metrics such as number of patches, patch density, Euclidian nearest-neighbor distance, mean patch size etc [34].

The other uncertainty related to scenario-design lies in the designation of exclusion levels. In our study the excluded value for certain areas in BAU and SGS scenarios was set to 80%. The question arises which number is the appropriate one since, if the demand for urban land increases and protection gets treated “more loosely”, the excluded areas could be assigned with even lower values. Finally, all these values had to be set arbitrarily. After all, scenarios are “possibilities, not predictions” [35]. The reality can be much more complex in a way that, in the example of our case, sprawled and compact growth increase or decrease at the same time.

Despite these uncertainties, SLEUTH has proven to be successful in providing us with insights regarding historic urban growth in the coastal area of Emilia-Romagna, as well as being practical in deriving scenarios of future urban growth. We found the code relatively easy to operate, and the fact that it is freely available online should not be disregarded. Although there is always a certain level of uncertainty in trajectories of future urban development, we believe that the outputs from SLEUTH scenarios can assist coastal planners in taking into account where urban development could take place in future. SLETH outputs could have an important role on the decision-making in coastal planning: GIF maps are highly compatible with Geographic Information Systems (GIS) and hence, suitable for further quantitative analysis. This compatibility can be taken as an advantage and utilized as a visualization tool with a potentially high l impact on different types of end-users.

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