Themistoklis Kontos<sup>1</sup> (Lecturer), Loukas Katikas<sup>2</sup> (Ph.D candidate), <sup>1</sup> University of the Aegean, Department of Environment, Greece, <sup>2</sup> National and Technical University of Athens, School of Rural and Surveying Engineering, Greece, <u>kontos@aegean.gr</u>, <u>loukaskatikas@gmail.com</u>

# Delimiting Future Urban Sprawl Boundaries Using a GIS-based Model for Ecological Sensitivity Index Assessment and Optimization Techniques. The case of Mytilene (Lesvos Island, Greece)

**Abstract** - Delimiting urban sprawl boundaries have been generally regarded as a regulatory policy measure for controlling chaotic and sparse urban expansion and for protecting ecological areas. The conservation of ecologically sensitive areas plays a key role in environmental protection; so, harmonizing urban sprawling with nature conservation can be viewed as a binary compatibility planning problem. This study, aims to employ a geographical allocation model, based on the minimization of the environmental cost in order to apply complex spatial clustering techniques. Firstly, five ecological sensitivity factors affecting the ecological footprint of the study area are modeled through Geographic Information Systems (GIS) and Analytic Hierarchy Process (AHP) method in order to evaluate the Ecological Sensitivity Index. Then, several spatial objectives and constraints such as continuity and compactness are applied and finally, the most optimal areas are extracted for future urban sprawl. Spatial regulations, sitting rules considerations and scenarios based on the parameters of the spatial clusters outputs are tested to the commune of Mytilene, located on Lesvos Island, Greece, where strong land use changes have been recorded by the urban sprawl over the last three decades.

<u>Index Terms</u>: Ecological Sensitivity, Land Use Modeling and Planning, Urban Sprawl Boundaries, Geographic Information Systems, Spatial Clustering and Optimization

## 1. INTRODUCTION

Nowadays, it is imperative to manage environmental protection in order to protect natural resources. We live in an era where the terms of sustainability and risk expressing the relationship between human - nature is an integral part of our daily lives and our duty is to ensure a balance between these two systems.

A crucial question is how can we measure the balance between human activities and environment in a sustainable manner? The evaluation of ecological importance in a regional scale is to emphasize on the harmonious development between production space, living space, and ecological space. Ecological risk assessment is conducted in order to transform scientific data into meaningful information about the risk of human activities to the environment. The purpose is to enable planners, risk managers, and stakeholders to make informed environmental decisions. A set of new technologies contributes in this direction, such as Geographic Information Systems (GIS) and Spatial Optimization models, which in combination with a broader set of disciplines can be a useful management tool to address the problem.

Goal programming approaches present many advantages compared to specific algorithms: simplicity of implementation if a programming software is available, reliability of the method, computational speed, exact or guaranteed approximate solution of the problem, and finally, possibility of easily modifying the model.

#### 2. LITERATURE REVIEW

## Environmental protection and land use management

Ecological importance evaluation towards the environmental protection is to explore the spatial distribution and provide measures for preventing ecological security issues from the regional development and construction (Xie et al., 2014). Among those measures developed for addressing cause-effect relationships relating the human and natural systems, the DPSIR (Driving Forces-Pressure-State-Impact-Response) has been established. In the DPSIR framework, there is a chain of causal links from 'driving forces' (human activities) over 'pressures' upon the environment (use and pollution) to environmental 'state' and 'impacts' on ecology and society finally leading to societal and political 'responses' (EEA, 1999). According to Spilanis et al. (2005, 1) "the construction of a practical tool for the maintenance and improvement of sustainability at a local level" is really important.

Integrated analysis has already applied for ecological environment security assessment. Shao et al. (2013)(2014) and Cen et al. (2015) developed a model of indicator selection and quantitative assessment to ensure urban ecological security comprehensively and dynamically. The ecological evaluation based on GIS was firstly proposed by McHarg in the 1980s (McHarg, 1981) who mentioned the need for a model which allows the examination of the impact of any plan upon the health of the inhabitants and the well – being of the social and natural systems. A couple of decades later, Steiner, McHarg's student, proposed a model of Environmentally Sensitive Areas (ESA) through a zonal planning that were regulated to offer an even higher level of protection (Steiner, 2000). In addition, Malczewski developed a multi-criteria method for the land suitability evaluation based on GIS (Malczewski et al., 2003). By 2010, Mingwu et al. (2010) applied two methods to analyze ecological sensitivity. Similar approaches specialized in urban ecological sensitivity evaluation system consisting four critical factors: a) vegetation, b) slope, c) elevation and d) rivers system (Huang et al. 2013) have been proposed as well as, on key factors of ecological sensitivity (e.g. geology, landform, hydrology, vegetation) (Yun et al. 2015).

#### **Optimization and Land Use Allocation**

Since land-use patterns are spatially explicit in nature, planning and management necessarily must integrate GIS, multi-criteria decision making and spatial optimization in meaningful ways if efficiency goals and objectives are to be achieved. In multi-objective optimization of land use (MOLU) models (Eastman et al. 1995; Aerts et al 2003), the commonly used objectives include the improvements related to compatibility and dependency among neighboring land uses, the suitability score of land units according to specific indices, compactness, natural value of landscape, urban development potential etc. (Masoomi et al. 2012). In particular, it has been used in facility location problems (Church 2002; Liu and Kao 2010; Kratika et al. 2014; Eiselt and Marianov 2015), ecological conservation models (Williams and ReVelle 1996; Snyder et al 2004; Costello and Polansky 2004; Billionnet 2013; Shao et al 2015; Beyer et al 2016;), suitability of land for agricultural use (Henseler et al. 2009; Hao et al. 2017), and regionalization problems and p-compact regions (Li et al 2014; Kim et al. 2015).

Therefore, efforts have been made to produce computationally tractable solutions by using various optimization techniques like: 1) integer programming (Kao and Lin 1996; Williams and ReVelle 1998; Aerts et al 2003; Shirable 2005; Ligmann-Zielinska 2008; Billionnet 2012; Liu and

Kao 2012; Beyer et al 2016), 2) heuristic methods based on a) genetic algorithms (Haque & Asami, 2011; Cao et al 2012; Datta et al 2012; Stewart and Janssen 2014; Mohammadi et al 2015;), b) simulated annealing (Stewart et al., 2004; Aerts et al 2005; Sante'-Riveira et al 2007) or c) particle swarm optimization (Liu et al 2012; Masoomi et al 2012; Sahebgharani 2016). It is important to highlight that the adoption of integer linear programming methods in land use management has been slow as long as early trials, tests and models proved unsatisfactory. The main reason was the lack of computing power when the size of the problem is spatially expanding (Williams and ReVelle 1998; Shirable 2005). Therefore, multiprocessing methods were applied to enforce IP model's capability through parallel computing environment (Liu and Kao 2012) and generative land-use modeling techniques enhanced with additional algorithms in order to solve the objectives faster (Ligmann-Zielinska et al. 2008). Contrary, heuristic algorithms are based on optimizing the objectives simultaneously in multi-objective mode focusing on Pareto front. Although, these methods do not generate an exact optimal solution, the generated solutions are meaningful and significant in many complex problems and case studies (Aerts et al. 2005).

Another important characteristic that characterizes MOLU is the structure of the input data and the ability the models have to interact with GIS. Many efforts have applied in recent years to combine spatial optimization procedures with GIS interfaces (Church 2002; Sante Riveira et al. (2008); Chen et al. 2010; Cao et al. 2012, Sanussi et al. 2014; Stewart and Janssen 2014; Mohammadi et al. 2015; Ligmann-Zielinska 2017). GIS make use of two types of data: grid data (raster format) and attribute data (vector format). Data in a raster model are stored in a twodimensional matrix of uniform cells on a regular grid. By their nature raster data are substantially easier to include in mathematical representations of the world for purposes of optimization. Using a grid-based representation of a planning region, Stewart et al. (2004) and Janssen et al. (2008) showed that it was possible to formulate a spatial planning problem in mathematical terms and apply MOLU to generate optimal solutions interactively.

#### Compactness, contiguity and spatial constraints

Compactness and as a result contiguity is an issue that belongs to *optimization spatial analysis* which in turn applies diverse analytic and computational techniques in order to find optimal or near to optimal solutions (Vanegas P. et al. 2010). Land-allocation models in terms of the method used to encourage compactness and contiguity are separated within two types of constructs: solution-based and explicit constraint-based. The explicit constraint approach may be further divided into adjacency-based clustering, perimeter-based compactness, and block aggregation (Ligmann-Zielinska et al. 2008).

Numerous techniques have already been implemented in order to calculate compactness, but the most common and effective methods are: 1) with Non-Linear Integer Programming (IP neighbor method) (Gabriel et al. (2006)), 2) Linear IP neighbor method (Kao and Lin 1996; Liu and Kao 2013), 3) Linear IP using buffer zones cells (Williams and ReVelle 1996), 4) Linear IP using aggregated blocks (Aerts et al. 2003; Stewart 2004;) 5) Minimization of shape index (Cao et al. 2012) and finally 6) Spatial autocorrelation (Moran's method) (Cao and Bo 2010).

Contiguity can be explicitly structured in spatial optimization models or implicitly accounted for in a solution algorithm. Most explicit approaches are based on graph theory imposing network connectivity (Williams 2002; Shirabe 2005; Datta et al. 2012; (Billionnet 2013). Williams

(2002) defined necessary and sufficient conditions for spatial connectivity. Rather than utilizing paths and spanning trees, Shirabe (2005) formulated contiguity constraints based on network flows. This work was extended by Duque et al. (2011) to include multiple network flows, one for each region. Datta et al. (2012) formalized their model as a multiobjective partitioning network problem using an Integer coded Genetic Algorithm.

#### **Urban sprawl management**

The increasing demand for land resources due to growth in population, urban areas, and economy has posed great challenges to rural and urban sustainable development in regional or national scale worldwide. (Haque and Asami 2014).

In recent years, great efforts have been succeeded on sustainable urban development and sprawl handling on the horizon of more compact and ecological friendly cities (Handayando et al. 2017). In particular, Kumar et al. (2016) with a Mixed Integer Quadratic Program (MIQP) consider just a single objective, maximizing suitability value of land to limit urban sprawl, based on two spatial constraints. Gabriel et al. (2006) on the contrary, take a multi-objective approach to controlling sprawl in land development by considering objectives from the perspective of the government, planners, environmentalists, conservationists, and land developers. Masoomi et al. (2012); Ma et al. (2017) and Handayando et al. (2017) include in their model similar objectives to achieve sustainable urban form areas.

The most comprehensive framework, according to the literature review, to quantify and measure sprawl is implemented more than a decade ago by Ewing et al. (2002). Based on cause-effect relationships of urban sprawl and quality of life, it includes numerous measures that are broadly divided into four categories, which are residential density, neighborhood mixture of homes, jobs, and services, strength of centers, such as business districts, and accessibility to the street network. Finally, Ligmann-Zielinska et al. (2008) developed probably the most robust optimization model for efficient utilization of urban space.

## 3. CONTRIBUTION OF THIS RESEARCH

Highlighting the most important factors in optimization procedures for land use management and ecological conservation the main purposes and contribution of this study are (1) to create a novel and integrated spatial index for evaluating and expressing the ecological sensitivity of a study area, (2) to demonstrate how the combination of theoretical models and GIS tools can contribute in environmental protection and land use management, (3) to develop a multiobjective land use allocation model for future urban sprawl boundaries expressed in a simple manner, (4) to achieve relevant computational time to obtain high quality and optimal compact sites through powerful programming techniques and finally (5) to incorporate these models into a GIS platform in order to be able to achieve multiple future scenarios and filtering out solutions as an interactive operation during a planning process.

## 4. MATERIALS AND METHODOLOGY

## **Study Area and Data**

The study area is the greater area of Mytilene, which is located in Lesvos Island in North-East Aegean Sea in Mediterranean Sea (*Fig.1*). The municipality covers an area of 107.5 km<sup>2</sup> with population of 37,890 inhabitants, according to the census of 2011. During the last three decades the land use changes regarding chaotic urban development lead to numerous impacts in the ecological and environmental status of the area. Data of land cover and ecosystem types were derived from the National Web Portal of Geospatial Data (<u>http://www.geodata.gov.gr/</u>). An extra spatial information added in Corine LC 2000 through digitalization as long as a lot of land use changes observed from 2000 to 2011. In order to create a detailed Digital Elevation Model (DEM) all the topographic elements (contours with contour interval 4 meters, heights, roads and drainage network) were digitized from maps of 1:5000 scale of the National and Geographical Military service.



## Methods

# **Ecological sensitivity model**

According to the related study of Troumbis (1995), the development of a mapping methodology assessing ecological sensitivity in natural systems, is an important condition to clarify the physical meaning of the term "ecological sensitivity". The term of "sensitivity" is not a specific variable and does not describe any physical property of a living system. Also, it can't be characterized by either as a single variable or as a complex descriptive parameter or factor which brings an etymological or conceptual dimension of the term "sensitivity". On the other hand, it is more accurate if we say that it is described as a pressure factor on natural systems, derived from human activities and is defined as a quality attribute that refers to the changes in the productivity and diversity of a natural system (mainly due to the land use changes) (*Fig. 2.*)

#### Combining ecological sensitivity model with GIS

The distinct steps of the framework are depicted in *Fig 2* and according to these steps the model of relative quantification of ecological sensitivity arises from the combination of the following parameters rated as presented in *Table 1.* and consist of: 1) Vegetation, 2) Drainage basin system, 3) Heterogeneity of ecological landscape, 4) Anthropogenic disturbance sources (e.g. settlements, transport networks) and 5) Topographic slope. Each land-use type is the basic of the model regarding the expression of the productivity and the diversity of the system. The graded hierarchy of the different types of vegetation in relation to the productivity and diversity is achieved by using specific weighted values which reflect the system's relative productivity and diversity amounts.

The other criteria are used to change – "affect" the initial value of vegetation's specific gravity through the addition or subtraction of weight's values. Therefore, the highest values correspond to the most diverse vegetation types which have a reliable water supply and are distant from sources of human disturbances. The lowest sensitivity values correspond to intensive agricultural areas and settlements (Troumbis 1995). These values from higher to lower mean high ecological sensitive areas (negative values), ecological sensitive (close to zero) and none ecological sensitive (positive values).



Figure 2. Geodatabase structure and procedural steps to determine the ecological sensitivity through GIS

### Evaluation of ecological sensitivity indicators weighting

As ecological sensitivity is a multi-attribute index, it often requires a method combining qualitative and quantitative analysis to evaluate. The analytical hierarchy process (AHP) is a decision-making method and a theory of measurement through pairwise comparisons and relies on the judgements of experts to derive priority scales. In the AHP method, obtaining the weights or priority vector of the alternatives or the criteria is required. The decision-making

process starts with defining and dividing the problem into issues-criteria, which may optionally be divided further to form a hierarchy of issues-elements (Saaty 2008).

Productivity - Diversity	Natural fracture type		Accessibility	<u>Slope</u>	
	Coniferous forests	8		30 - 50%	-1
	Wetland	8		> 50%	-2
	Sclerophyll vegetation	7		0 – 30%	0
	Mixed forests	7	Landscape Heter.	Number of natural structures types	
	Other forests types	7		No natural structure	0
	Broad leaved forests	7		2 types	1
	Olive trees	6		3 types	2
	Grasslands	5		More than 3 types	3
	Fruit trees and Scrublands	4	Drainage systems	Proximity to streams	
	Agricultural lands with	4		Periodic flow river of 4 <sup>th</sup> class	
	natural vegetation areas				
	Farms crops	3		Distance 0-100m	6
	Human settlements	0		Distance 101-200m	4
	Mining complex areas	0		Periodic flow river of 3rd class	
	Industrial zones	-1		Distance 0-50m	3
	Airports	-2		Periodic flow river of 2 <sup>nd</sup> class	
Anthropogenic disturbances	<u>Proximity to Road Network</u>			Distance 0-25m	2
	Small highways			Periodic flow river of 1st class	
	Distance 0-500m	-6		Distance 0-10m	1
	Distance 500-1000m	-5			
	Regional roads network		Table 1: Sub-criteria rankings		
	Distance 0-200m	-4			
	Distance 200-500m	-3			
	Gravel roads				
	Distance 0-100m	-2			
	Forest roads				
	Distance 0-50m	-1			

# **Optimization model**

Formulating an optimization problem generally contains three basic steps: defining decision variable(s), formulating objective function(s) and defining problem constraint(s). The model is non-linear if the objective function and/or some of the constraints are non-linear. Moreover, Gabriel et al. (2006) highlight in their model the class of quadratic problems as part of non-linear problems, however, the relaxed version of these problems are simply convex, quadratic programs with linear constraints and thus represent a reasonable computational burden given the state of the art in optimization solvers. In order to solve multiobjective optimization problem two main processes can be applied in general, (1) the weighting method and (2) the constrained method (Gabriel et al. 2006). Our algorithm is based on an Integer Quadratically Constrained optimization problem and Brunch and Bound algorithm upon linear constraints and weighted method approach, implemented through Gurobi optimization package (Gurobi Optimization 2017).

#### Size, data and complexity of the study area

In our model, as we referred to the literature, raster based formatted files are used (e.g. TIFF images) which are transformed into arrays as input for the optimization algorithm. Each raster cell represents ecological sensitivity index value. The dataset used as input for the model, in raster format, contains 287.028 cells (603 rows \* 476 columns) with a cell size of 30 meters.

Compactness calculation for each cell is affected by neighbored cell's state related to ecological sensitivity index. For our model, we express as neighborhood of a cell the twodimensional square lattice composed of a central cell and its four adjacent cells (Von Neumman Neighborhood) (Fotakis and Sidiropoulos 2012). Among the total number of cells, NoData values of the raster file are not included but the model is capable to handle them in spite of the fact that these values do not participate in the final optimal solution. These can include borders, backgrounds, the sea or other data considered to not have valid values.

Therefore, we have to customize the model to be able to search for an optimal solution above or near the boundary cells of the study area considering that the initial input raster is expressed as  $C_{i,j}$  for *i* as the total number of rows and *j* as the total number of columns. In order to be able to account cross defined neighbors for the cells above the coastline we must add two additional rows and columns forming a final raster dataset  $X_{i,j}$  for i = i + 2 and j = j + 2. Finally, the IQCP model contains 115.345 discrete variables (binary) and 232.414 constraints.

#### **Decision variables, Objectives and Constraints**

Minimum ecological sensitivity index: Ecological sensitivity index, and therefore, suitability of a land cell for urban growth is expressed as the status of location condition as it has formulated by MCA from previous steps. We apply multiple factor model of weighted summation to do the superposition calculation, ecological sensitivity index can be expressed by the following formula:

$$ES = \sum_{i=1}^{5} w_i f_i \qquad (1)$$

where ES is the ecological sensitivity index,  $w_i$  is the weight of each criteria *i* and  $f_i$  is the rating of criteria *i*.

Maximum compactness of urban growth patterns: A customized approach is applied for calculating compactness and continuity of cells based on Kao and Lin's (1996) model. In this study, compactness index is expressed as the total perimeter of the non-connected edges of the total cells leading the model to make urban patches regular and more rectangular. The continuity of the selected cells of the solution to the above model is guaranteed because the model seeks the smallest perimeter.

*Multiple factors optimization:* For a problem with consideration of multiple factors, the objective function of the model should be modified adding the weight factor of each objective and can be expressed as:

$$Minimize = \sum_{i=1}^{I} \sum_{j=1}^{J} (w_{s} * S_{ij} * x_{ij} + w_{u} * x_{ij} * V_{ij}) \quad (2)$$

where:

$$V_{ij} = 4 - (x_{i,j-1} + x_{i,j+1} + x_{i-1,j} + x_{i+1,j})$$
(3)

where *I* and *J* are the total number of rows and columns of cells;  $w_u$  is the weight for compactness and  $w_s$  is the weight for ecological sensitivity.  $S_{i,j}$  represents the value of ES (*Eq.* <u>1</u>) for each cell ,  $V_{i,j}$  is used to record the length of each cells perimeter;  $x_{i,j}$  , an [0,1] indicator variable, is defined to represent whether cell *i*,*j* belongs to a considered site or not.

Optimization constraints: The two fundamental constraints for our model refer indirectly to  $(\underline{Eq. 4})$  compactness calculation and neighbors accounting, NoData cell values handling and  $(\underline{Eq. 5})$  number of total amount of selected cells by the user, in order to calculate the objectives.

$$\sum_{i=1}^{l} \sum_{j=1}^{l} x_{i,j} = N$$
 (4)

subject to:

*N* as total cells selected for Urban Sprawl boundaries development for  $\forall I \in \{0, ..., i+1\}; \forall J \in \{0, ..., j+1\}$ 

$$\sum_{i=1}^{I} \sum_{j=1}^{J} x_{i,j} = N$$
 (5)

subject to:

N (total cells) for  $\forall I \in \{1, \ldots, i\}; \forall J \in \{1, \ldots, j\}$ 

where:

N is the required size (in numbers of cells) of the desired site;

### 5. <u>RESULTS</u>

### Sub – criteria

The visualization output of each sub-criterion is shown in <u>Fig.4</u> where the final maps of land use, road and drainage network proximity, slope and heterogeneity index are demonstrated.

Productivity and Diversity index: The most downgraded land units are observed in the central part of the study area as also to the South - East coastal part where urban sprawl areas and other individual industries are located. In contrary, the most productive areas are observed in North –West and South – East part of the study area where different types of forests, wetlands and sclerophyll vegetation exist. Proximity to disturbance sources index: The higher disturbance values exist because of the small highways that connect the city of Mytilene with the entire island as also the regional road network of the municipality that connects the different smaller settlements and covers the biggest area. Proximity to streams index: The drainage network was divided in different classes according to Stahler's method of designating stream orders (Strahler 1957). The biggest the stream order and the proximity is, the higher values of the index are observed. Landscape Heterogeneity index: Landscape diversity calculated to study the local landscape heterogeneity by drawing out a grid of 500m cell size and dimensions of 38\*29 cells. Heterogeneity index reflects the diversity of the amounts of landscape elements, apart from areas with continuous urban development and the variation of their proportion. The higher the combination of different vegetation types is observed the less vulnerable is an ecosystem as long as the ecological footprint increases. Accessibility index: Higher slope values reduce ecosystem's regenerative potential as long as the capability of humans to intervene (e.g. forest fires) is decreased. The most vulnerable areas are observed in the South – East part of the municipality as the mountain area of Amali is located.



# Weight determination and Ecological Sensitivity index

According to the calculation results derived from AHP, if CR < 0.1, where CR is the consistency ratio, the matrix is deemed to have the satisfactory consistency otherwise it should be adjusted. In our case, CR = 0,059 so the consistency value is accepted for number of criteria n = 5,  $\lambda$ max is the biggest eigenvalue, random inconsistency RI = 1,12 and consistency index CI = 0,067 (Malczewski 2008). The last step is to transform the ecological sensitivity single factor layers into the final raster map. The final results are presented in <u>Fig.5 (no.1)</u> where the ecological sensitivity index is calculated for the study area. Scale of the cell values ranges between -9 and 16, as a result, most downgraded areas are expressed with red and orange colors. Contrary, the most ecologically upgraded and stable areas are visualized with different green patterns.

#### **Urban Sprawl Boundaries results**

Multiple scenarios of future urban growth patterns are presented in Fig.5 for number of total selected cells N = 100, 500 and 1000 in order to validate model's capability to allocate continuous and compact patterns related to the given weighting factors for ecological sensitivity and compactness. For small patterns (N=100) model returns absolutely squared areas irrespective of each criteria's weight. Searching for larger areas (N=500 and 1000) it is highlighted that as long as compactness weighting factor is maximized (>=0.6) contiguity and compactness are guaranteed. Although, is noted that for large clusters as compactness weight reduces (<=0.6), final optimal areas might be fragmented (e.g. in two separate clusters), something that seems normal considering that contiguity and compactness are expressed through the objective function and not as constraint factors.



Figure.5. (1) Ecological Sensitivity map and (2), (3), (4), (5), (6) Future Urban Sprawl Boundaries for one cluster selection. Scenario (2): 100 cells, weights (Comp/ES) 0.5/0.5, Scenario (3): 500 cells, weights 0.7/0.3, Scenario (4): 500 cells, weights 0.8/0.2, Scenario (5): 1000 cells, weights 0.7/0.3, Scenario (6): 1000 cells,

### 6. CONCLUSION AND DISCUSSION

This study developed a goal programming-based framework with the integration of a multicriteria ecological assessment and external planning interventions, which aims to generate future urban sprawl land sites that minimize ecological sensitivity and compactness. The main modifications include: (1) include a different measure of ecological sensitivity; (2) implement a novel approach of formatting and calculating compactness (3) implement all these through a fast and easily handled model based on Integer Non-Linear programming.

Therefore, an integer quadratic constrained programming (IQCP) model for urban sprawl boundaries allocation was formulated. One of the main advantages of our approach is that it produces solutions that reflect precisely the default preferences of the user. Furthermore, it relies on a rigorous and systematic mathematical approach that avoids falling in sub-optimal solutions leading to optimal contiguous and compact sites in a promising amount of time considering the size of the spatial units. Future research consists of multiple clustering options (return more than one cluster), additional sitting objectives and constraints and a fully compatible toolbox with GIS platforms.

#### **REFERENCES**

Aerts, J. C. J. H., Eisinger E., Heuvelink G.B.M., Stewart T.J., (2003), Using Linear Integer Programming for Multi-site Land-use Allocation, Journal in Geographical Analysis, vol. 35, pp. 148 – 169.

Aerts J.C.J.H, Herwijnen M.V., Janssen R., Stewart T.J. (2005), Evaluating Spatial Design Techniques for Solving Land-use Allocation Problems, Journal of Environmenta Planning and Management, vol. 48, no. 1, pp. 121 - 142

Beyer H.L., Dujardin Y., Watts M.E., Possingham H.P., (2016), Solving conservation planning problems with integer linear programming, Journal in Ecological Modelling, vol. 328, pp. 14 - 22

Billionnet A., (2012), Designing an optimal connectd nature reserve, Journal in Applied Mathematical Modeling, vol. 36, pp. 2213 - 2223

Billionnet A. (2013), Mathematical optimization ideas for biodiversity conservation, Journal in European Journal of Operational Research, vol. 231, pp. 514 - 534

Boroushaki S., Malczewski J.(2008), Implementing an extension of the analytical hierarchy process using ordered weighted averaging operators with fuzzy quantifiers in ArcGis, Computers & Geosciences, Vol.34, Issue 4, pg. 399 - 410

Cao K., Bo H., (2010), Comparison of Spatial Compactness Evaluation methods for Simple Genetic Algorithm based Land Use Planning Optimization problem, The International Archives of the Photogrammetry, Journal in Remote Sensing and Spatial Information Sciences, vol. 38, Part II

Cao K., Huang B., Wang S. Lin H., (2012), Sustainable land use optimization using Boundary-based Fast Genetic Algorithm, Journal in Computers, Environment and Urban Systems, vol. 36, pp. 257 – 269.

Cen X., Wu C., Xing X., Fang M., Garang Z., Wu Y., (2015), Coupling Intensive Land Use and Landscape Ecological Security for Urban Sustainability: An Integrated Socioeconomic Data and Spatial Metrics Analysis in Hangzhou City, Journal in Sustainability, vol. 7, pp. 1459 - 1482

Church R.L. (2002), Geographical information systems and location science, Journal in Computers and Operations Research, vol. 29, pp. 541 – 562

Costello C., Polansky S. (2004), Dynamic reserves site selection, Journal in Resource and Energy Economics, vol. 26, pp. 157 - 174

Eastman J.R., Jin W., Kyem P.A.K, Toledano J., (1995), Raster procedures for multi-criteria/multi-objective decisions, Journal in Photogrammetric Engineering and Remote Sensing, vol. 61, pp. 539 – 547

EEA, (1999), Environmental Indicators: Typology and Overview, European Environmental Agency, 19pp Eiselt H.A, Marianov V., (2015), Location modeling for municipal solid waste facilities, Journal in Computers and Operations Research, vol. 62, pp. 305 - 315

Ewing R., Pendal R., Chen D., (2002), Measuring sprawl and its impact, Technical Report Smart Growth America, Washington D.C

Fotakis D., Sidiropoulos E., (2012), Combined land-use and water allocation planning, Journal in Annals of Operations Research, vol. 219 (1), pp. 169 - 185

Gabriel S.A, Faria J.A, Moglen G.E, (2006), A multi-objective approach to smart growth in land development, Journal in Socio-Economic Planning Sciences, vol. 40, pp. 212 - 248

Gurobi Optimization, Inc. Gurobi Optimizer Reference Manual Version 7.5./ Gurobi Optimizer Version 7.5.2. Houston, Texas: Gurobi Optimization, Inc., April 2010. (software program) Houston, Texas: Gurobi Optimization, 2017

Janssen, R., van Herwijnen, M., Stewart, T. J., Aerts, J. C. J. H., (2008), Multiobjective decision support for land use planning. Environment and Planning B: Planning and Design, vol. 35, pp. 740 - 756.

Janssen, R., Arciniegas, G. A., Verhoeven, J. T. A., (2013), Spatial evaluation of ecological qualities to support interactive design of land use plans. Environment and Planning B: Planning and Design, vol. 40, pp. 427 - 446.

Hammad A.W.A., Akbarnezhad A., Rey D., (2016), A multi-objective mixed integer nonlinear programming model for construction site layout planning to minimize noise pollution and transport costs, Journal in Automation in Construction, vol. 61, pp. 73-85

Hao L., Su X., Singh V.P., Ayantobo O.O., (2017), Spatial Optimization of Agricultural Land Use Based on Cross-Entropy Method, Entropy 2017, 19,592.

Haque A., Asami Y. (2014), Optimizing urban land use allocation for planners and real estate developers, Journal in Computers, Environment and Urban Systems, vol. 46, pp. 57 - 69

Henseler, M., Wirsig, A., Herrmann S. Krimly T., Dabbert, S., (2009), Modeling the impact of global change on regional agricultural land use through an activity-based non-linear programming approach. Agricultural Systems, vol. 100, pp. 31–42.

Huang T., Cheng S. G., Hu Z. X., (2013), The Urban Ecological Sensitivity Analysis of Enshi city Based on GIS and Analytic Hierarchy Process Model, Advanced Materials Research, Vols. 671 – 674, pp 2599 – 2603.

Kim K., Dean D.J., Kim H., Chun Y., (2015), Spatial optimization for regionalization problems with spatial interaction: a heuristic approach, International Journal of Geographical Information Science, doi: 10.1080/13658816.2015.1031671

Kratikca J., Dugošija D., Savic' A., (2014), A new mixed integer linear programming model for the level uncapacitated facility location problem, Journal in Applied Mathematical Modelling, vol. 38, pp. 2118 - 2129

Kumar P., Rosenberger J.M., Daud Iqbal G.M., (2016), Mixed integer linear programming approaches for land use planning that limit urban sprawl, Journal in Computers and Industrial Engineering, vol. 102, pp. 33 - 43

Li W., Church R.L., Goodchild M.F., (2014), An extendable heuristic framework to solve the p-compactregions problem for urban economic modeling, Journal at Computers, Environment and Urban Systems, vol. 43, pp. 1 - 13

Ligmann-Zielinska A., Church R.L., Jankwski P., (2008), Spatial optimization as a generative technique for sustainable multiobjective land-use allocation, International Journal of Geographical Information Science, vol.22, no.6, pp. 601-622

Liu K.H, Kao J.J, (2012), Parallelized branch-and-bound algorithm for raster-based landfill siting, Journal in Civil Engineering and Environmental Systems, vol.30, no. 1, pp. 15 - 25

Liu Y., Wang H., Ji Y., Liu Z., Zhao X., (2012), Land Use Zoning at the County Level Based on a Multi-Objective Particle Swarm Optimization Algorithm: A Case Study from Yicheng, China, International Journal of Environmental Research and Public Health, vol. 9, pp. 2801 - 2826

McHarg I. L., (1981), Human ecological planning at Pensylvania, Landscape Planning 8, 109 – 120.

Mingwu Z., Haijiang J., Desuo C., Chunbo G., (2010), The comparative study on the ecological sensitivity analysis in Huixian karst wetland, China, International Society for Environmental Information Sciences, Annual Conference (ISEIS).

Nunneri, C. (2007). Linking Ecological and Socio-economic Systems Analysis – A methodological approach based on Ecological Risk, Berichte aus dem Forschungs- und Technologiezentrum Westküste, No. 45, Büsum 2007

Sante'-Riveira I., Boullo'n-Maga'n M., Crecente-Maseda, Miranda-Barro's D., (2008), Algorithm based on simulated annealing for land-use allocation, Journal in Computers and Geosciences, vol.34, pp. 259 - 268 Shao C., Tian X., Guan Y., Ju M., Xie Q., (2013), Development and Application of a New Grey Dynamic Hierarchy Analysis System (GDHAS) for Evaluating Urban Ecological Security, Journal in International Journal of Environmental Research and Public Health, vol. 10, pp. 2084 - 2108

Shao C. et al. (2014), Trends Analysis of Ecological Environment Security based on DPSIR Model in the Coastal zone: A survey study in Tianjin, China, Int. J. Environ. Res 8 (3), pg. 765 - 778

Shao J, Yang L., Peng L., Chi T., Wang X., (2015), An Improved Artificial Bee Colony-Based Approach for Zoning Protected Ecological Areas, PLoS ONE 10(9): e0137880

Yun S., Shal G., Wenbao M., Wei S., (2015), Analysis of the Ecological Sensitivity of Pengyang County based on Key Factors, The Open Biotechnology Journal, 9, pg. 21 – 26

Snyder S.A., Haight R.G., ReVelle C.S (2004), A scenario optimization model for dynamic reserve site selection, Journal in Environmental Modeling and Assessment, vol. 9, pp. 179 - 187

Spilanis I., Kizos T., Kondili J., Koulouri M., Vakoufaris H., (2005), Sustainability measurement in islands: The case of South Aegean island, Greece, Biodiversity Conservation and Sustainable Development in Mountain Areas of Europe, Conference, Greece, Ioannina, 20-24 September

Steiner, F., (2000). A watershed at a watershed: the potential for environmentally sensitive area protection in the upper San Pedro Srainage Basin (Mexico and USA). Landscape Urban Plann. 129–148.

Stewart, T. J., Janssen, R., van Herwijnen, M., (2004), A genetic algorithm approach to multiobjective land use planning. Computers and Operations Research, vol. 32, pp. 2293 - 2313.

Troumbis A., (1995), Ecological networks in Greece: Current status, administration approaches and research initiatives, Landschap vol. 12 (3), pp. 51 – 62.

Williams J.C., ReVelle C.S., (1996), A 0-1 programming approach to delineating protected reserves, Journal in Environment and Planning B: Planning and Design, vol. 23, pp. 607 - 624

Vanegas P., Cattrysse D, Orshven J. V. (2010), Compactness in Spatial Decision Support: A Literature Review, D. Taniar et al. (Eds.): ICCSA 2010, Part I, LNCS 6016, Springer – Verlag Berlin Heidelberg, pp. 414 – 419

Vaskan P., Passuello A., Gosalbez G.G., Schumacher M., (2013), Combined use of GIS and mixed-integer linear programming for identifying optimal agricultural areas for sewage sludge amendment: A case study of Catalonia, Journal in Environmental Modelling and Software, vol. 46, pp. 163 – 169.

Xie H., Yao G., Liu G., (2014), Spatial evaluation of the ecological importance based on a GIS for environmental management: A case study in Xingguo county of China, Journal in Ecological Indicators, vol. 51, pp. 3 - 12.