ADDRESSING COMPLEX SPATIAL DECISION PROBLEMS IN MOUNTAINOUS AREAS: THE INTELLIGENT SPATIAL DECISION SUPPORT SYSTEMS (SDSS) APPROACH

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Abstract
This paper discusses the issue of land use planning and land policy making for mountain regions, considered as regions with specific characteristics (natural, cultural, etc.), but also development constraints. Spatial decision making in such regions is characterized by complexity (semi-structured spatial decision problems) and multiplicity of problems. These indicate the need for qualitative information in support of the decision-making process, in order to improve effectiveness in decision making. Toward this end, it is first presented the state-of-the-art of MC-SDSSs and their significance as a planning tools for mountainous areas; second are outlined the multiple benefits from the use of Artificial Intelligence (AI) tools in the context of MC-SDSS for Multisite Land Use Allocation (MLUA) procedures applied in mountainous areas; and finally, a MLUAL methodological framework as the core of a future MC-SDSS is proposed.

Keywords: *MC-SDSS, mountainous areas, spatial planning, decision making, artificial intelligence*
JEL classification: **R10, R11**

1. Introduction: Mountainous Areas

According to Diaz et al. [6], mountains are amongst the most fragile environments in the world. The world's mountain areas cover 24% of the Earth's land surface [14] and are home to 12% of the global population (Huddleston et al. [13]). A further 14% of the global population is estimated to live in the vicinity of their surrounding areas (Meybeck et al. [26]).

A far greater proportion of the global population relies on the goods and services provided by these areas, particularly water, which can be vital for agriculture, communities and for industries that are even located hundreds or thousands of kilometers away from the mountains. As urbanization continues to increase in the world, the mountains are also key centers for recreation and tourism; their attraction is often heightened by their remarkably high levels of biodiversity (Messerli and Ives [25]). Furthermore, they are also of major importance in shaping regional climates of the surrounding areas. Currently, these environments are affected by different pressures from economic and population growth. Quantitative data about global mountainous areas (km2) are presented in Fig. 1, according to the classification of the World Mountain Map of UNEP-WCMC (United Nations Environmental Program-World Conservation Monitoring Centre).

The focus of the present paper is on the development of a methodological framework for addressing complex spatial decision problems in mountainous areas. In this respect, in Section 2 is discussed the context of spatial planning in mountainous areas in Greece. In Section 3 is presented the state-of-the-art of MC-SDSSs and their significance as planning tools for mountainous areas. Section 4 focuses on the MC-SDSS for Spatial Planning in Mountainous Areas, where are outlined the multiple benefits from the use of Artificial Intelligence (AI) tools in the context of MC-SDSS for Multisite Land Use Allocation (MLUA) procedures, applied in mountainous areas. In Section 5 is proposed a MLUAL methodological framework, using AI techniques, as the core of a future MC-SDSS for coping with complex spatial decision problems in mountainous areas. Finally, in Section 6 some conclusions are drawn.

1.1. Europe's mountainous areas

In the ESDP [8] mountain areas are characterized as unprotected and environmentally sensitive areas. Europe's mountains are of vital importance to the continent's population in many ways, and have been described as 'the undervalued ecological backbone of Europe" (EEA [9]). The mountains of Europe, just as elsewhere, are connected to the biological and cultural diversity of their geographical environment. They are the home of many of Europe's ethnic minorities, with specific cultures, languages or dialects and traditions. However, this remarkable cultural diversity is gradually being weakened in many areas, by external influences and the diminishing local populations, especially among the younger generations. This affects not only mountain people's sense of identity, but also the ways in which they use the landscape, the crops they grow, and the food they produce (Nordic Center for Spatial Development [27]). According to UNEP-WCMC analysis approach, Europe's mountainous areas cover a total land of approximately 2.2 million km^2 (Fig. 2).

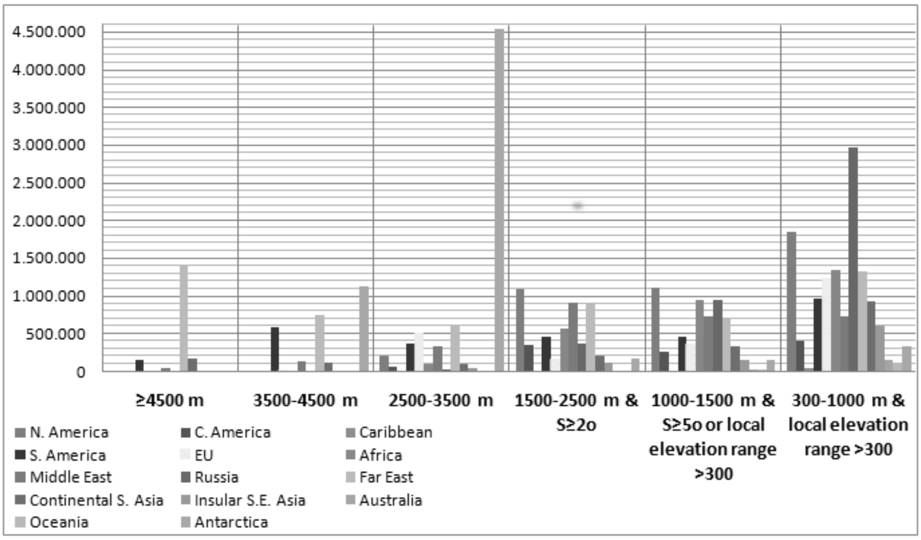

Figure 1: Global mountainous areas statistics by region[3]

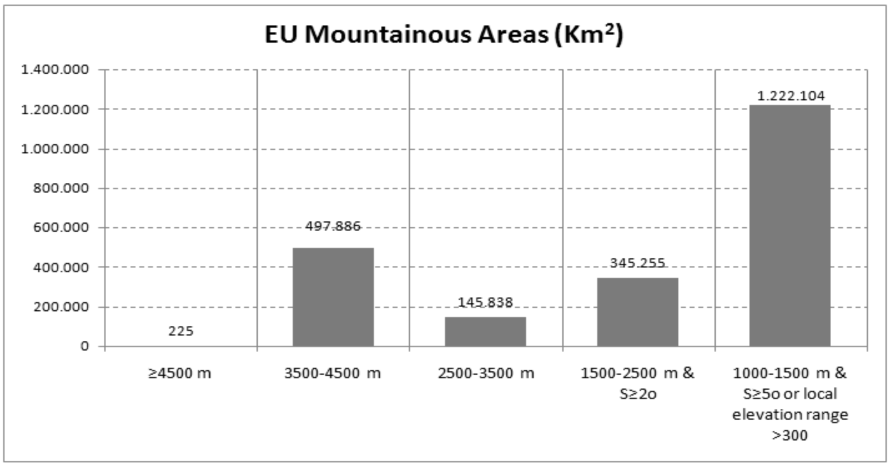

Figure 2: Europe's mountainous areas (km^2)

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[3] *Adopted from: http://quin.unep-wcmc.org/habitats/mountains/statistics.htm*

The ‘ideal world’ of mountain areas is now threatened by socio-economic shifts, increasing negative impacts of tourism and traffic and other changes in land use. In the Accession Countries, more mountain areas are expected to become endangered through rapid economic development (EEA [9]).

Greece is one of the most mountainous countries in EU. According to the Hellenic Statistical Authority (2001), approximately 70.5 % of total country area is mountainous (42.0%), and semi-mountainous areas (28.5 %). Recent results from the Nordic Center of Spatial Development [27] indicate a greater percentage of approximately 78.0% of the total country area (Tolidis et al. [35]). The following are some basic issues concerning the Greek mountain profile:

- An intense abandonment in the past due to urbanization (Figure 3). Nowadays, the situation is reversed due to the fact that citizens who expect a better quality of life and more profitable occupation opportunities are returning to rural areas.
- Multidimensional interdependence and interaction of natural and socio-economic reality that lead to attractive areas which appeal to tourists.
- Conflicts over land use, due to lack of specific strategic land use allocation and local spatial plans (See Section 2).

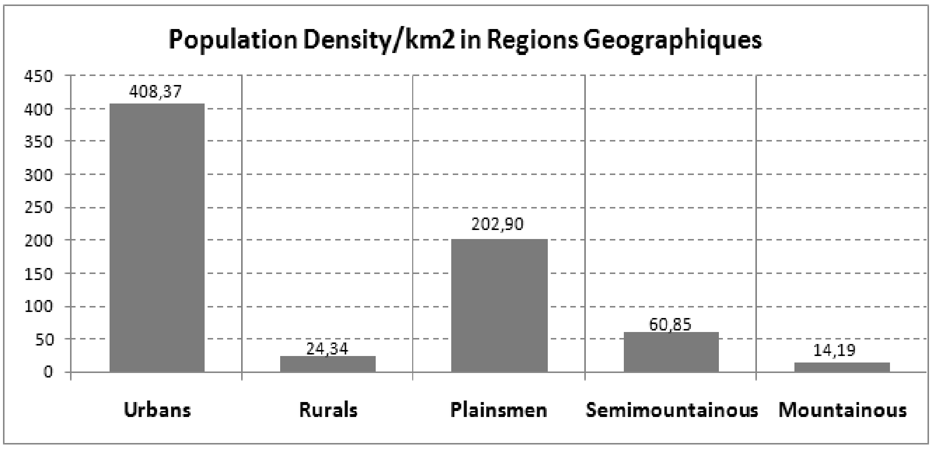

Figure 3: Population density/Km^2 in different types of Greek regions

2. Spatial Planning in Mountainous Areas: Greece

Mountains have been directly addressed in few policy documents. In general, every policy action should consider the network of direct and indirect interactions which is affected by the relevant policy. For mountain areas, it is crucial to adopt a comprehensive, spatially-integrated policy which is able to reflect and support multi-functionality, which has been the sustainable concept regarding mountains for many generations. Spatial and urban planning in Greece is a fundamental tool for decision making to define strategy for land development and to secure economic growth, social stability, environmental protection and quality of life (Potsiou and Muller [29]).

At the national level, the responsible authority for spatial planning in Greece is the Ministry of Environment, Energy and Climate Change, who provides the spatial planning legislation and the strategic framework, comprising of a variety of laws, plans and regulations. The establishment of the law 2742/99 for national and regional spatial planning provided two main planning instruments (Serraos et al. [31]:1) The “General Framework for Spatial Planning and Sustainable Development” (GFSPSD) and 2) The “Special Frameworks for Spatial Planning and Sustainable Development” (SFSPSD). The GFSPSD consists of a national territorial plan and SFSPSD of sectoral territorial plans. Furthermore, the “Regional Frameworks for Spatial Planning and Sustainable Development” (RFSPSD), which constitute practically Regional Territorial Plans, play a central role among the spatial planning instruments at the Regional level, according to the Law 2742/99. The Greek Spatial Planning System can be schematically presented in the following flowchart, organized by planning levels (Figure 4).

The goals which are directly connected to space and consist of the content of Greek spatial development are[4] (Tolidis et al. [35]) the development of a balanced and polycentric urban system and a new urban– rural relationship, b) securing equal access to infrastructure and knowledge, c) sustainable development, wise management and protection of nature and cultural heritage. According to the "National Framework for Strategic Development-ESPA" (implementation period: 2007-2013), the strategic development of mountainous areas mainly aims at restructuring production and habitation. Although the GFSPSD recognizes the importance and the need for further specialization of the strategic choices and priorities of planning in mountainous areas, there is a lack of specific legislative guidelines and planning framework for mountains. Furthermore, Greek Spatial Planning at a local scale (municipalities) is implemented by the "General Urban Plans-GUP" and "Open City Spatial and Housing Organization Plans-OCSHOP", which are basically the "tools" for local spatial plan implementations. However, only 4% of the total municipalities' local spatial plans have been established (Tolidis et al. [35])[5].

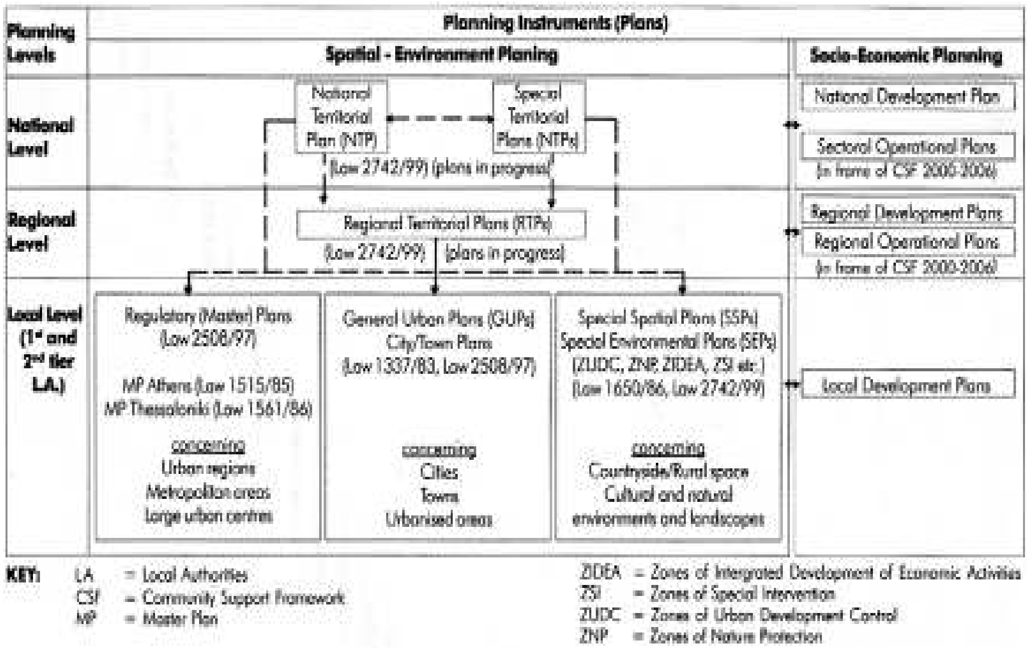

Figure 4: The general Greek Spatial-Environment Planning System (Beriatos [2])

3. Spatial Decision Support Systems-SDSS

3.1. Spatial decision-making process

A decision can be defined as a choice that is made between two or more alternatives. Any decision-making problem falls upon a continuum that ranges from completely structured to unstructured decisions (Malczewski [19]). The structured decisions can be programmed and solved by a computer. The structured problems are repetitive and routine, and the computer can solve the structured problem without requiring any intervention from a decision maker. The unstructured decisions must be solved by decision makers without assistance from a computer. In this case the decision makers use their experience.

According to Malczewski [19], they employ heuristic and common knowledge that involve the narrowing down of the field of search, for a solution, by reasoning on past experience of similar problems. Most real-life decision problems can be found somewhere among the above extreme cases of completely structured and unstructured decisions. These decisions are called semi-structured and can be solved by decision makers with computer support. Furthermore, for most decision

[4] *Not in compliance with policy guidelines for the spatial development of EU.*

[5] *According to statistics from 2010.*

situations, the spatial decision problems are ill-structured because of the variety of interest groups and uncertainties associated with assessment and evaluation of the distribution of the quality and quantity of impacts at alternative locations (Malczewski [19]). These semi-structured problems are often multidimensional, with goals and objectives that are not completely defined, and have a large number of alternative solutions (Gao et al. [12]).

Also, the types of spatial decisions can be organized into four main categories (Kemp [15]): (a) site selection, (b) location allocation, (c) land use selection, and (d) land use allocation. The great complexity involved in spatial decision making suggests the use of automated or computer-based techniques. However, there is usually not a single solution that meets all objectives for all stakeholders (Xiao [37]).

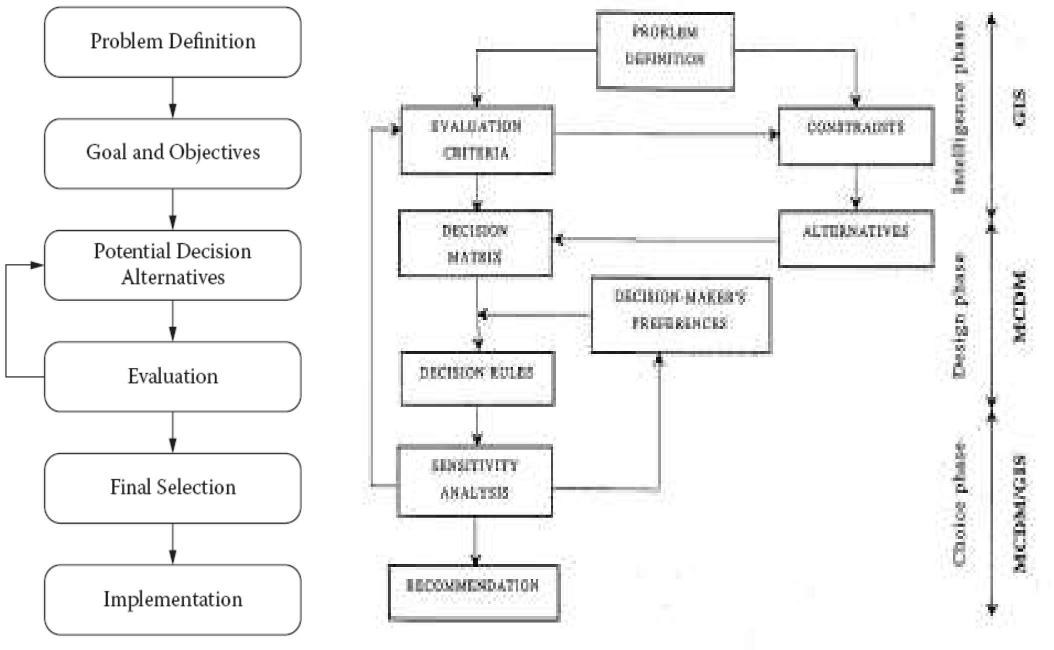

Figure 5: General Spatial Decision Making Process (left) and Spatial Multi-criteria Decision Analysis (right)

Considering the above comments, it is more obvious that the spatial decision-making process is basically a Multi-Criteria Decision Making Process (MCDMP). In particular, spatial multi-criteria decision problems, typically involve a set of geographically-defined alternatives (events) from which a choice of one or more alternatives is made, with respect to a given set of evaluation criteria (Malczewski [19]). Spatial multi-criteria analysis requires information on criterion values and the geographical locations of alternatives in addition to the decision makers' preferences with respect to a set of evaluation criteria. In Figure 5, the general spatial-decision making process as proposed by Sugumaran and DeGroote [33] and the spatial multi-criteria decision analysis as proposed by Malczewski [19] are shown.

It should be noted that:

- Spatial decision problems are indeed complex and ill-structured (semi-structured), because of the variety of interested groups and uncertainties associated with the assessment and evaluation of the distribution of the quality and quantity of impacts at alternative locations.
- Greek Spatial Planning at a local scale (municipalities) implemented by the 'General Urban Plans-GUP' and 'Open City Spatial and Housing Organization Plans-OCSHOP', but there is a lack of specific legislation guidelines and planning framework for mountains.

- The *mountainous areas are "warehouses"* of cultural and natural resources, with specific socioeconomic features, multidimensional human geography and are characterized also by multidimensional interdependence and interaction of natural, cultural and socio-economic reality and
- Both spatial and temporal analyses have to become more complex[6] by the decision makers in order to improve spatial decisions.

There is added value in the implementation of Spatial Multi-criteria Decision Analysis (S-MCDA) techniques for Spatial Planning in Mountainous areas at local scale (municipalities) supported by "smart" geographical databases aiming to capture the decision maker's expectations.

3.2. SDSS: overview, characteristics and trends

The systemic approach is crucial and it's the main feature of an optimum methodological approach for supporting decisions related to solving semi-structured spatial problems in planning processes. It has proved to be the most suitable demarche to analyze the system and to formalize the relations and interactions between the system components. The systemic approach consists of developing the models closer to reality, and therefore is able to apprehend the complexity of the system by formalizing the interactions between its components (Bouloiz et al. [3]). The use of Spatial Decision Support Systems (SDSS) has grown dramatically over the last few decades, but there is still no universally accepted definition. An SDSS must be built to be flexible to accommodate various stakeholder preferences and restrictions and allow for effective user interaction in an iterative problem-solving environment (Sugumaran and de Groote [33]). According to Malczewski [19] an SDSS aims to improve the effectiveness of decision making by incorporating decision-maker judgments and computer-based programs within the decision making-process. The purpose of such a system is to support a decision maker in making "better" decisions. Furthermore, the structure of SDSSs can be described by identifying the major components or subsystems of the system. An SDSS typically contains three genetic components (Malczewski [19]): a) A Database Management System (DBMS) and geographical database; b) A Model-Based Management System (MBMS) and model base; and c) A Dialogue Generation and Management System (DGMS).

3.2.1. Multi-Criteria spatial decision support systems (MC-SDSSs)

The multi-criteria problem is at the core of decision support. MC-SDSS can be viewed as a spatial Decision Support System (DSS). The essential difference between these two concepts is that MC-SDSSs emphasize the multi-criteria character of spatial decision making. In general, the main feature of an MC-SDSS is the integration of GIS capabilities and Multi-criteria Decision Making (MCDM) techniques (Malczewski [19]). MC-SDSSs offer a flexible, problem solving environment where the decision problem can be explored, understood and redefined; Tradeoffs between multiple and conflicting objectives are investigated and priority actions are set (Ascough et al. [1]). The basic structure of an MC-SDSS is composed of three main elements as shown in the following diagram (Figure 6).

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[6] Complexity is the combination of a whole whose elements are combined in a way which is not immediately clear in the analysis (LeMoigne [16]).

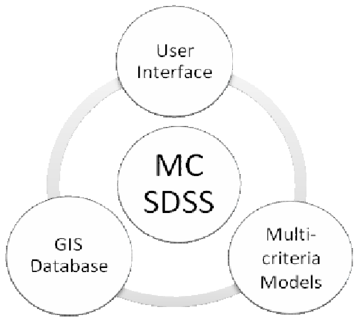

Figure 6: Basic structure of Multi-Criteria Spatial Decision Support Systems (MC-SDSS)

In a review of literature on SDSS publication per year, Sugumaran and DeGroote [33] showed that approximately 72% of SDSS publications came after 2000. These are similar to the results in a review of literature on GIS-based Multi-criteria Decision Analysis, by Malczewski [21], who found that 70% of reviewed articles were published after 1999 (see Fig. 7).

4. MC-SDSS for Spatial Planning in Mountainous Areas

In order to move on to the next framework analysis on the use of MC-SDSSs for spatial planning in mountainous areas, the following assumptions need to be considered:

- Mountains must be considered as a *separate geographic unity* in the strategic spatial plans and spatial decision problems, especially for mountainous areas, *which are very complex and ill-structured (semi-structured).*
- Spatial planning of mountainous areas is crucial for preserving the natural, cultural and human environment and consists of one of *the major processes of an integrated spatial policy.*

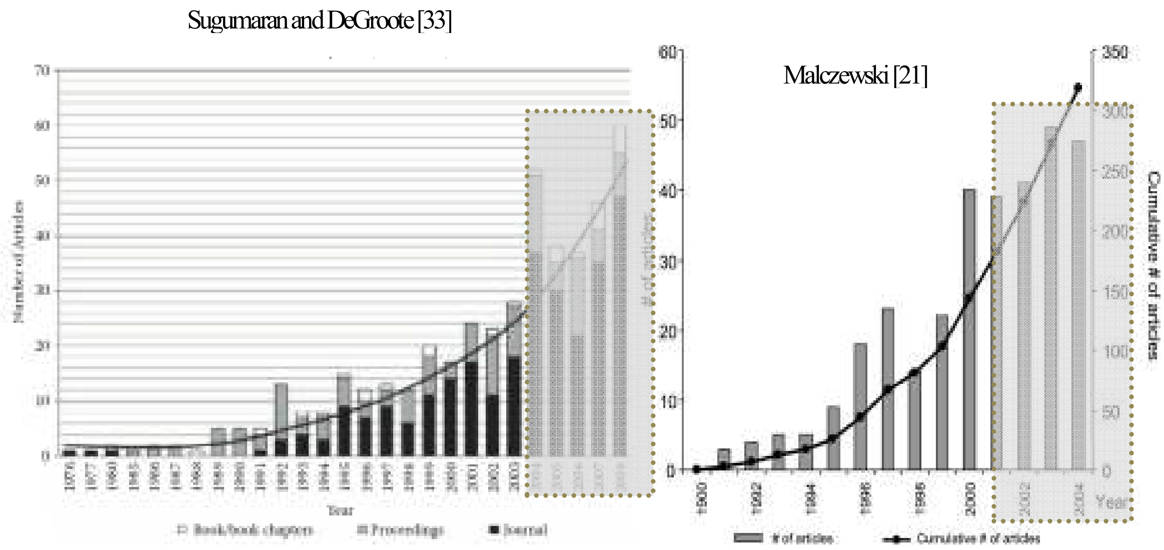

Figure 7: SDSS Publication/Year (1978-2008) (left) and Total Number of GIS and MCDM articles/year (1990-2004) (right)

- The spatial planning process and policies for mountain areas must be based on a thorough understanding of the *spatiotemporal changes* of social, economic, cultural and environmental reality, as well as the inherent problems due to their particular characteristics and development constraints.

- Due to the fact that the features in mountain areas vary spatially (development degree, human geography, socio-economic reality, relations of dependency and interaction with other areas-regions), *the local scale of spatial planning* (municipalities) seems to be the most appropriate.
- Apparently, *the main trend of actual European landscape changes* relates to the polarization between a more intensive use of land in most favourable areas and a more extensive use, or even land abandonment, in remote rural areas having less favourable economic and environmental conditions such as mountain areas.
- MC-SDSS can be used to *bridge the gap between policy makers and complex computerized models* aiming to improve the effectiveness of decision making of mountainous areas spatial problems.
- Multisite Land Use Allocation (MLUA) is crucial for the integrated development of mountainous areas (problem of allocating more than one land use type in a given area). According to Stewart et al. [32] this is a complex process, as in land use, planning decisions must be made not only on what to do (selection of activities) but also on where to do it, adding a whole extra class of decision variables to the problem.
- In Greece there is additional value in using MC-SDSS, due to the fact that *there is a lack of land use allocation in mountainous areas*, resulting in conflicts which in future will become more intensive. (See Section 2.2).
- An integrated MC-SDSS for MLUA in mountain areas should incorporate features related to the spatiotemporal analysis of external entities outside geographic boundaries of the study area. Hereby, external entities include the natural, cultural and anthropogenic environment, as well as the regional planning guidelines affected by or affecting the MLUA process.

4.1. Rationale behind the development of MC-SDSS for MLUA in mountainous areas

An integrated MC-SDSS for MLUA in mountainous areas must be characterized by the ability for both spatial and temporal analysis in order to better represent the reality by a modeling approach. Moreover, according to Ascough [1], multi-criteria spatial decision support tools must be capable of dealing with uncertainty. Also, a key feature of such a prototype system is the ability to predict the spatial pattern of a mountainous area for a given MLUA plan both in local and regional scale aiming to answer the following questions:

- What if the proposed LUAL plan is implemented (spatiotemporal evolution)?
- What are the spatial implications of the local plan at regional level?
- What is the risk of the final decision making at environmental, cultural, human geography and socio-economic level in and outside the boundaries of the study areas?

Developing a MC-SDSS for MLUA is a complex process in which, during the design phase, the following questions must be answered in order to proceed to the development and implementation phase:

- Who will use the system (single-user, group of users etc.)?
- Would it be a desktop or Web-based SDSS?
- Which is the spatial scale of planning?
- What spatiotemporal methods will be provided for the user/users?
- What kind of data (quantity and quality) should be used?
- Which are the geographical database characteristics?
- What strategy must be chosen for coupling GIS and spatial modeling systems (loose or tight)?
- Modeling techniques?
- Functionalities by the user interface?
- Sensitivity analysis techniques?

Although the above questions are the basis of the development of a prototype MC-SDSS for MLUA in mountainous regions, the core of such a system, refers to the computational techniques that can help in modeling and describing complex systems for inference and decision making. Regarding the assumptions and the rationale behind the development of a MC-

SDSS for MLUA in mountainous areas, we strongly believe that Artificial Intelligence Techniques (AI-computational techniques) when incorporated in a MC-SDSS, provide various benefits for both spatiotemporal analysis and spatial planning in the context of an Intelligent MC-SDSS (Fig. 8). In particular, for MLUA in mountainous areas, these techniques offer new opportunities for more complex analysis, with an improved representation of the reality and predictions.

According to Malczewski [20], AI seeks to develop systems that attempt to mimic human intelligence without claiming an understanding of the underlying processes. The common denominator of AI methods is that, unlike conventional approaches, they are tolerant of imprecision, ambiguity, uncertainty, and partial truth. During the last decade prominent research areas in developing hybrid systems include the integration of GIS and AI approaches such as Fuzzy Logic (FL), Genetic Algorithms (GAs), Artificial Neural Networks (ANNs), Cellular Automata (CA) and Agent-Based Modeling (ABM). The current surveys on coupling SDSS and AI have been focused on the evaluation of the accuracy of these techniques, especially when used to solve complex spatial planning and land use allocation problems.

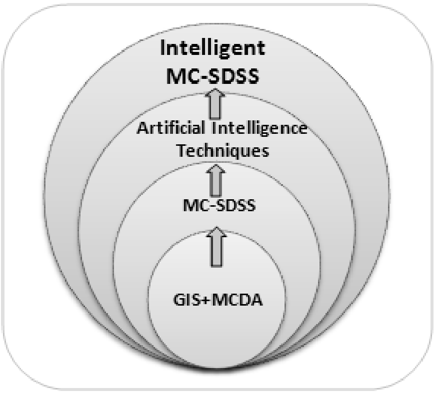

Figure 8: Framework of an Intelligent MC-SDSS for MLUA in mountainous areas

4.2. AI Techniques in Spatial Planning

4.2.1. Fuzzy Logic

The conventional methods based on Boolean algebra are unable to provide the precise numerical information required in complex land-use suitability analysis [20]. The inclusion of crisp boundaries in spatial and non spatial data produces similar definitive or crisp results in any modeling or SDSS activity (Sugumaran and DeGroote [33]). The fuzzy set theory allows objects or locations to belong partially to multiple sets instead of being completely discrete (Malczewski [19]). The Fuzzy set theory can also be used for linguistic statements that are used to provide an ordering of criteria such as low, moderate, and high.

4.2.2. Genetic Algorithms (GAs)

Genetic algorithms are search methods that mimic biological evolution in that they involve a competitive selection that eliminates poor solutions (Malczewski [20]). These types of algorithms have been used commonly in land use planning and suitability analyses (Malczewski [20]). Brooks [4] demonstrated that generic algorithm can improve the conventional land-use suitability approaches by its capability to identify a specific site for locating activities. Matthews et al. [24] suggested that a GA can be a key component of the land-use planning and management support system. Parolo et al. [28] propose a new model for optimizing the allocation of tourist infrastructures (refuges and camping sites), and apply it to a protected area in the European Alps. To reach this goal, a complex model based on genetic algorithms was required (instead of a common multi-criteria analysis), to obtain a complex interplay in the form of a dynamical simulation, where candidate solutions are interactively evaluated. Stewart et al. [31] provide a mathematical formulation for the land use planning problem, and motivate and develop a goal programming/reference point methodology for incorporating multiple objectives into its solution. This formulation gives rise to a nonlinear combinatorial optimization problem, for which a GA was developed.

4.2.3. Artificial Neural Networks (ANNs)

Malczewski [20] points out that it is convenient to think of neural networks in terms of the following three steps: input (e.g. data for land use analysis), model (e.g. model of land use), and output (e.g. the best pattern of land use). In a neural network procedure, each input is presented into the network during a training phase, where the network is told the correct output for each given set of inputs. The network is presented by many of these input and output sets, and it begins identifying the relationships between the data. Like a brain, the memory or 'knowledge' of the resulting network is stored in the overall pattern of connections that determine the network's structure. Neural networks approximate solutions to complex land-use suitability problems, rather than provide deterministic solutions (Fischer [11]). A neural network can be seen as an adaptive system that progressively organizes itself, in order to arrive at an approximate solution. It has the capability of progressively improving its performance on a given task, by somehow 'learning' how to do the task better. Thus, the approach does not require the analyst to specify accurately and unambiguously the steps towards solutions. According to Malczewski [20], the problem with neural networks is that it is not clear what constitutes the optimal structure of the network. He characterizes the nature of the ANN methods as a 'black box' which is a limitation as far as real-world applications are concerned.

4.2.4. Cellular Automata (CA)

A CA is a discrete dynamic system composed of a set of cells in a one-or multidimensional lattice. The state of each cell in the regular spatial lattice depends on its previous state and the state of the cells in its neighbourhood (Malczewski [20]). The CA data structure is very analogous to the GIS raster data model (Sugumaran and DeGroote [33]). Cellular automata methods are inherently spatial and are among the simplest representations of dynamic systems, and because of this, it can be very useful for modeling land use dynamics [36]. Sugumaran and DeGroote [33] point out that weakness of CA techniques is that they are based on neighbourhood relationships and generally does not account for global effects that also affect spatial phenomena. Mathey et al. [23] developed a decentralized spatial decision support tool for forest management planning, based on cellular automata (CA) modeling. An innovation of this model is that beyond spatially allocating/simulating management activities, the CA rules and state space are modified to allow cells to co-evolve until a plan for all periods of the planning horizon has been achieved.

4.2.5. Agent-Based Modeling (ABM)

The main concept of ABM is that it captures the observed behaviour of organized complex systems by using fine-grained entities (the agents) that represent the main drivers of changes in the state of the system. All agents are structurally coupled to an environment and to each other by a set of rules. In principle, each agent "behaves" autonomously. The reactive or proactive behaviour of individual agents is determined by rules and based on reasoning about observations of agents of its environment. The cumulative effect of the individual behaviour of agents is a global change in the state of the environment (Ligtenberg et al. [18]). The rationale of this approach is that it is easier to model the behaviour of individuals than it is to model a system as a whole. However, by modeling the behaviour of individual agents, system-level lessons can be discovered (Sugumaran and DeGroote [33]). Ligtenberg et al. [18] designed a method to generate insights that can improve the understanding of the behaviour of socio-spatial systems in a planning context. The method was tested by carrying out an experimental role play to validate individual agent tasks, focusing on the ability of agents to generate beliefs and preferences about their environment. In addition, an earlier study of Ligtenberg et al. [17] describes a spatial planning model combining a multi-agent simulation (MAS) approach with cellular automata (CA). The model includes individual actor behaviour according to bottom-up modeling concept.

5. Process Concept of MLUA in Mountainous Areas

Taking into consideration all the above, in this section we intend to propose a schematic methodology approach for MLUA in mountainous areas, using AI techniques in the terms of a MC-Spatial Decision Support System. Although there is no case study application, it's an analytic methodology flowchart providing the main steps and its expected results as the core of a future MC-SDSS.

As already mentioned, Land Use Allocation (LUA) process is a very complex procedure, especially in mountainous areas, due to inherent environmental, socio-economic and anthropogeography characteristics and interactions which, in the terms of modeling, lead to very sensitive systems. It is obvious that changing an existing spatial pattern, by introducing new or changing existing land uses, could lead to "new" local development realities. Furthermore, the MLUA process increases the decision difficulty because decision-maker/s in the early stages must provide robust answers for two main questions regarding the types of land uses: "Where?" and "What?" to plan and in the final stages of the question "What if?" Regarding these challenges, mountain land must be evaluated in the terms of 'land use capability' and 'land use suitability' for a set of alternative land uses.

The term 'Land Use Capability-LUC', introduced in 1960 by the Soil Conservation Service in USA and has been widely used, especially in the American Continent [5] "Capability" is viewed by some as the inherent capacity of land to perform at a given level for a general use, and "suitability" as a statement of the adaptability of a given area for a specific kind of land use; others see capability as a classification of land primarily in relation to degradation hazards, whilst some regard the terms 'suitability' and 'capability' as interchangeable (FAO [10]). In literature, few studies consider this separation in land evaluation procedures and, in most cases, the 'Land Use Capability' is used as a spatial indicator to evaluate agricultural land uses. A recent example is the study of Tenerelli and Carver [34] who set-up a GIS based multi-criteria approach to assess a range of possibilities for perennial energy crops conversion by applying a land capability model and describing the suitability of the land for energy crop growth. The model is based on a multicriteria evaluation (MCE), which assesses the suitable area and the capability level for energy crops by considering pedo-climatic and topographic diagnostic criteria.

In this study, the general methodology is composed of three different phases. LUC evaluation and classification is used not only for evaluating agricultural land uses but also for any proposed land use type. In the overall MLUA procedure LUC is an intermediate phase. In preliminary stage, advanced spatiotemporal analyses must take place, in order to support the decision maker to define specific regions, where interventions are needed. Further spatial choices (e.g. regional, national etc), existing plans and legislation are also considered in this stage, to recognize spatial constraints, limitations and general spatial development directives (see Section 2) for the study area. Table 1 presents further details about this preliminary phase (Phase A).

Through this stage, the decision-maker is able to:

- Identify the spatial problems related to the existing land use patterns (e.g. land use conflicts).
- Formulate alternative land use scenarios and to define its main objectives and sub-objectives. Each of these scenarios consists of a set of main and sub land use types (Fig. 9).

Table 1: Description of the preliminary phase

Phase A: Preliminary Spatiotemporal Analyses and Simulation				
Sub-stages	**Description/Details**	**Tools and AI Techniques**	**Expected Results**	**Expected Outputs**
A1	Evaluation of existing Land Use Pattern	Remote Sensing. Spatial Statistics, GIS, Fuzzy Logic	Land use index	Land use map
A2	Existing spatial plans, legislations and directives	GIS and literature	Spatial constraints and limitations, spatial development directives	Constraints/Limitation Maps. Spatial Development Directions Maps (classified)
A3	Spatiotemporal analyses of existing land use pattern (past to present) (at least 30 years ago).	GIS, Remote sensing, spatial statistics, Cellular Automata (CA). Agent-based Modelling (AMB). Case-Based Reasoning (CBR)	Spatial Dynamics Simulation. Land use types evaluation in the overall development profile of the study area.	Temporal Maps of Land Uses.
A4	Future forecast of the existing land use pattern.	GIS, Artificial Neural Networks (ANN). Case-Based Reasoning (CBR)	Problem definition and identification of regions which need to be examined in the terms of Land Use planning.	Map of specific regions for Land Use Allocation

Artificial Intelligent (AI) techniques are necessary almost in every sub-stage. Furthermore, this stage is crucial in the overall MLUA process, where the expected outputs from sub-stage A4 are the inputs for the next stage of LUC evaluation.

Moving on the next phase (Phase B: Land Use Capability Evaluation) a first set of allocation criteria, which consists of constraints (exclusionary criteria) and capability factors (non-exclusionary criteria) need to be determined, regarding only the Main Land Use types (MUij) of alternative scenarios proposed in the first phase. A classified map will be produced for its main land use type, in compliance with the evaluation criteria where the land capability classes reflect degrees of capability. A sample of classes presented in Table 2. This stage requires good knowledge and expertise relevant to the requirements of every land use type and especially to the factors which impact the allocation procedure. Otherwise, a sub-database including qualitative and quantitative information about various land use types should be integrated into the main SDSS database.

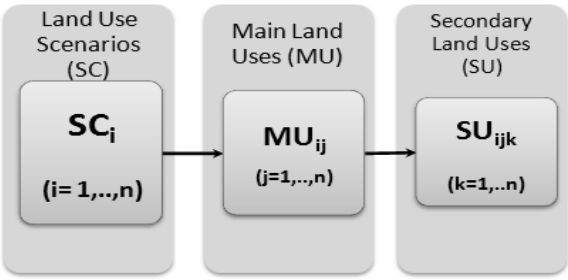

Figure 9: Scenarios and land use types' structure

The expected outputs from this phase are land use capability classification maps of each MU (MUij) according to the scenarios proposed by first phase. The methodology approach comprised the following steps (Dimopoulou et al. [7]):

Table 2: Sample of capability classes

Classes	Description
1	Land having no significant limitations to sustained application of a given use, or only minor limitations that will not significantly reduce productivity or benefits and will not raise inputs above an acceptable level.
2	Land having limitations which in aggregate are moderately severe for sustained application of a given use; the limitations will reduce productivity or benefits and increase required inputs to the extent that the overall advantage to be gained from the use, although still attractive, will be appreciably inferior to that expected on Class 1 land
3	Land having limitations which in aggregate are severe for sustained application of a given use and will so reduce productivity or benefits, or increase required inputs, that this expenditure will be only marginally justified

- Using buffer zoning excluded areas are indicated, i.e. sub-regions where a specific land use type cannot be located according to the constraints applied. Overlay of buffer maps of various thematic layers to identify and represent areas of constraints. Constraining criteria remain as Boolean images, dividing the study area in two land categories, i.e., capable (capability index 1) and uncapable (capability index 0). The mathematical formula using exclusionary criteria only, is:

$$CI = \prod_{j=1}^{K} bj$$

  where: CI = overall capability index value (0 or 1); b_j = capability index value for each constraining criterion (0 or 1); K = number of constraining criteria.
- Creation of classified maps for each factor (non exclusionary criteria) using appropriate grid cell size.
- Weights assignation to each factor according to their relative impact on every MU allocation. For an objective weight assignment process, a pair wise comparison can be applied in the context of the Analytical Hierarchy Process (AHP) decision-making process (Saaty [30]) or the Order Weighted Averaging (OWA) approach (Malczewski [22]).
- The final capability maps for every MU, evaluation are formed by overlaying the maps produced from step 1 and 3. The mathematical form for the assignment of the overall capability index, applying both exclusionary (constraints) and non-exclusionary (factors) criteria, is:

$$CI = \sum_{i=1}^{N} w_i x_i \times \prod_{j=1}^{K} bj$$

  where: CI = overall capability index value; w_i = weight of factor i; x_i = criterion score of factor i; b_j = criterion score of constraint j; N = number of factors; K = number of constraining criteria.

Finally, in the third phase (Phase C: Land Use Suitability Evaluation) a second set of allocation criteria are applied, regarding the Sub Land Use types (SUijk) of every MU type (MUij). These criteria are divided into constraints and factors and are based on more specific local scale conditions of the study area. A classified map will be produced for its SUijk, in compliance with the allocation criteria, where the land suitability classes reflect degrees of suitability. The expected outputs from this phase are land use suitability classification maps of each SU (SUij). The methodology approach comprises the same steps with the land use capability evaluation procedure. The mathematical form for the assignment of the overall suitability index, applying both exclusionary (constraints) and non-exclusionary (factors) criteria, is:

$$SI = \sum_{i=1}^{N} w_i x_i \times \prod_{j=1}^{K} bj$$

where: SI = overall suitability index value; w_i = weight of factor i; x_i = criterion score of factor i; b_j = criterion score of constraint j; N = number of factors; K = number of constraining criteria.

Final Land Use Map can be resulted from and aggregation procedure using both the Land Use Capability and Suitability Maps. The mathematical form is:

$$FI = \sum_{ij=1}^{N} CI_{ij} \times \sum_{ijk=1}^{K} SI_{ijk}$$

where: FI = overall allocation index value; N = number of Main Land Uses (MU); K = number of Sub Land Use types (LU), CI_{ij}= Capability Index of MU_{ij}, SI_{ijk}=Suitability Index of SU_{ijk}.

The final land use map can be used as an input in the Sub-stage A4 (see Table 5.1) in order to predict spatiotemporal evolution of the proposed land use plan. The overall MLUAL methodology is presented in the following flowchart (Fig. 10) according to the phases described above. Among others, sensitivity analyses it has been integrated in the overall methodology approach.

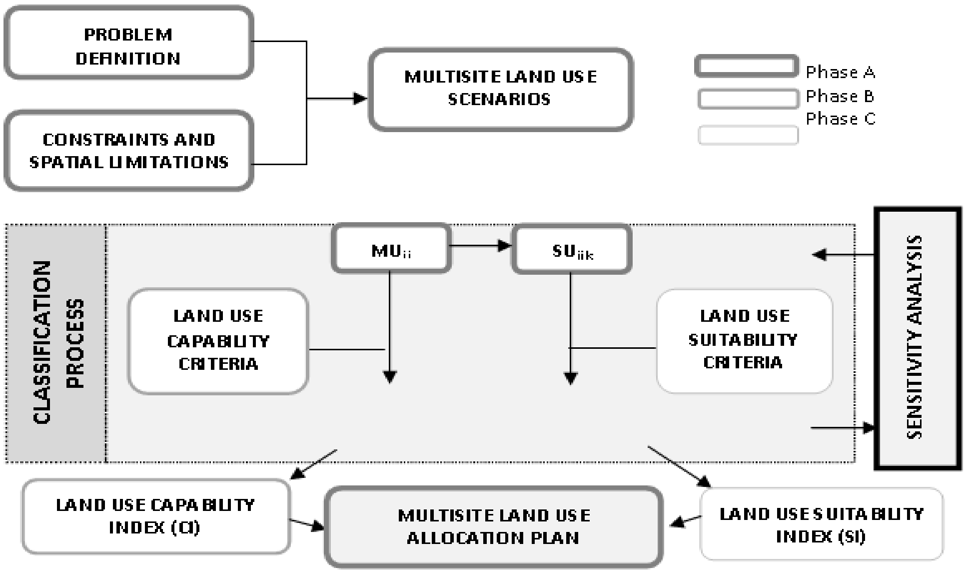

Figure 10: Overall MLUAL methodology flowchart

6. Executive Summary and Conclusions

There is no doubt that spatial problems vary depending on the features of the wider environment in which they are located (natural, cultural, socioeconomic, and anthropogenic). In particular, spatial decision problems, especially for mountainous areas, are very complex and ill-structured (semi-structured) and it is crucial to adopt a comprehensive, spatially integrated policy which is able to reflect and support the multi-functionality which has been the sustainable concept in mountains for many generations. Spatial planning of mountainous areas is also crucial for preserving the natural, cultural and human environment and consists of one of the major processes of an integrated spatial policy. Moreover, the spatial planning process and policies for mountain areas must be based on a thorough understanding of the spatiotemporal changes of social, economic, cultural and environmental reality as well as the inherent problems due to their particular characteristics and development constraints. Consequently, the modern decision-maker must be supported by Multi-criteria Spatial Decision Support Systems (MC-SDSS) in order to make improved spatial planning decisions. Especially for mountainous areas, the basis for an integrated development is the implementation of an effective Multisite Land Use Allocation (MLUA) plan aiming to: preserve their complex environment (natural, cultural, socioeconomic and anthropogenic), to avoid land use conflicts and to achieve a balanced spatial development simultaneously.

An integrated MC-SDSS for MLUA in mountainous areas must be characterized by the ability for both spatial and temporal analysis in order to better represent the reality by a modeling approach. The core of such a prototype system refers to the computational techniques that can help in modeling and describing complex systems for inference and decision making. Also, a key feature of such a system is the ability to predict the spatial pattern of a mountainous area for a given MLUA plan both in local and regional scale. Regarding the assumptions and the rationale behind the development of a MC-SDSS for MLUA in mountainous areas, we strongly believe that Artificial Intelligence Techniques (Fuzzy Logic, Genetic Algorithms, Artificial Neural Networks, Cellular Automata and Agent-Based Simulation), when incorporated in a MC-SDSS, provides various benefits for both spatiotemporal analysis and spatial planning in the context of an Intelligent MC-SDSS.

To deal with the above challenges, the proposed process concept of MLUAL in mountainous areas introduces a new methodological approach, by dividing the land use evaluation process into land use capability and suitability assessment. The rationale behind this approach is that, for every proposed land use plan scenario, a set of main and secondary land uses are defined. Regarding the fact that, a land use type affects, directly or indirectly, the spatial development profile of both the case study area and the neighbour areas (in the terms of land use policy), the main land use types (MUij) are equal to strategic choices of an integrated spatial development plan. Therefore, the allocation criteria (constraints and factors) of these kinds of land use types should satisfy the broader spatial strategic objectives set for the study area. In the other hand, the sub land use types (SUijk) evaluation expands the allocation analysis to a more detailed level, using special local allocation criteria. Classified maps are produced according to the capability and suitability degree of every main and sub land use type respectively and a final land use map can be resulted from an aggregation procedure.

Artificial Intelligence (AI) techniques for land analysis are incorporated in the overall process mainly in two phases: In a preliminary stage, AI techniques are suggested for performing complex spatiotemporal analyses by the decision maker. The expected results and outputs support the decisions that are need to be taken, regarding the definition of spatial problems and constraints/limitation. Furthermore, every final proposed MLUAL plan (See Fig.5.2) can be spatiotemporally evaluated using appropriate AI techniques and the results can be used as a feedback for the overall process.

Although there is a trend in coupling AI techniques with spatial modeling, there is a lack of studies concerning the incorporation of these techniques into MC-SDSS for developing hybrid systems. The latter is the main subject of our current research which is focusing on the evaluation of the described methodological approach for MLUAL in mountainous areas.

References

1. Ascough, J.C., Rector, H.D., Hoag, D.L., McMaster, G.S., Vandenberg, B.C., Shaffer, M.J., Weltz, M.A., Ahuja, L.R. (2002), Multicriteria Spatial Decision Support Systems: Overview, Applications, and Future Research Directions. Online Proceedings of the *International Environmental Modelling and Software Society Conference on Integrated Assessment and Decision Support* 3:175–180 <http://www.iemss.org/iemss2002/>.
2. Beriatos, E. (2002), Planning in Greece, Special Bulletin in the Frame of the 38th International Planning Congress, Athens.
3. Bouloiz, H., Garbolino, E. and Tkiouat, M. (2010), Contribution of a Systemic Modeling Approach Applied to Support Risk Analysis of a Storage Unit of Chemical Products in Morocco. *Journal of Loss Prevention in the Process Industries* 23:312-322.
4. Brookes, C.J. (1997), A Parameterized Region-growing Programme for Site Allocation on Raster Suitability Maps. *International Journal of Geographical Information Science* 11:375–396.
5. Comerma, J. (2010), Land Capability, Suitability and Vocation in Venezuela, 19th World Congress of Soil Science, *Soil Solutions for a Changing World*, 1 – 6 August 2010, Brisbane, Australia.

6. Diaz, H.F., Grosjean, M. and Graumlich, L. (2003), Climate Variability and Change in High Elevation Regions: Past, Present and Future. *Climatic Change* 59:1–4.
7. Dimopoulou, E., Tolidis, K., Orfanoudakis, Y. and Adam, K. (2011), Spatial Multi-criteria Decision Analysis for Site Selection of Sustainable Stone Waste Disposal, Proceedings of 3rd International Conference on Environmental Management, Engineering, Planning and Economics (CEMEPE 2011) & SECOTOX Conference, Skiathos, 19-24/7/2011,Greece, pp. 461-466.
8. European Commission (1997), European Spatial Development Perspective, First Official Draft, Presented at the Informal Meeting of Ministers responsible for Spatial Planning of the Member States of the European Union, Noordwijk, 9-10 June 1997. Office for Official Publications of the European Communities, Luxembourg.
9. European Environment Agency (EEA) (1999), Environment in the European Union at the Turn of the Century, Environmental Assessment Report No 2, Office for Official Publications of the European Communities, Luxembourg.
10. FAO (1976), A Framework for Land Evaluation, *FAO Soils Bulletin*, 32, ISBN 92-5-100111-1
11. Fischer, M.M. (1994), From Conventional to Knowledge-based Geographic Information Systems. Computers. *Environment and Urban Systems* 18:233–242.
12. Gao, S., Sundaram, D. and Paynter, J. (2004), Flexible Support for Spatial Decision Making, *37th Annual International Conference on System Sciences*, Honolulu, Hawaii. <http://ec.europa.eu/regional_policy/sources/docgener/studies/study_en.htm> <http://www.ntua.gr/MIRC/6th_conference/presentations/1_main_sessions/6th_session/TOLIDIS%20K%20-%20KALOGIROU%20C-%20DIMOPOULOU%20E.pdf>
13. Huddleston, B. et al (2003), *Towards a GIS-based Analysis of Mountain Environments and Populations*. FAO, Rome.
14. Kapos, V., Rhind, J. Edwards, M., Ravilious, C. and Price, M.F. (2000), Developing a Map of the World's Mountain and Forests, *Forests in Sustainable Mountain Development: A State-of-Knowledge Report for 2000*. CAB International, Wallingford.
15. Kemp, K. (2008), *Encyclopedia of Geographic Information Science*. SAGE Publications, IncLondon.
16. Le Moigne, J.L. (1994), *La théorie du système général, théorie de la modélisation*. 4th ed.
17. Ligtenberg, A., Bregt, A. and Lammeren, R. (2001), Multi-actor-based Land Use Modeling: Spatial Planning using Agents. *Landscape and Urban Planning* 56:21-33.
18. Ligtenberg, A., Lammeren, R., Bregt, A. and Beulens, A. (2010), Validation of an Agent-based Model for Spatial Planning: A Role-playing Approach, Computers. *Environment and Urban Systems* 34:424–434.
19. Malczewski, J. (1999) *GIS and Multicriteria Decision Analysis*, New York: John Wiley & Sons, Inc.
20. Malczewski, J. (2004), GIS-based Land-use Suitability Analysis: A Critical Overview. *Progress in Planning* 62:3–65.
21. Malczewski, J. (2006a), GIS-based Multicriteria Decision Analysis: A Survey of the Literature. *International Journal of Geographical Information Science* 20:703–726.
22. Malczewski, J. (2006b), Ordered Weighted Averaging with Fuzzy Quantifiers: GIS-based Multicriteria Evaluation for Land-use Suitability Analysis. *International Journal of Applied Earth Observations and Geoinformation* 8:270–277.
23. Mathey, A., Krcmar, E., Dragicevic, S. and Vertinsky, I. (2008), An Object-oriented Cellular Automata Model for Forest Planning Problems, E*cological Modelling* 212:359–371.

24. Matthews, K.B., Craw, S., MacKenzie, I., Elder, S. and Sibbald, A.R. (1999), Applying Genetic Algorithms to Land Use Planning, *18th Workshop of the UK Planning and Scheduling Special Interest Group*, University of Salford, UK, 15th-16th December, 109–115.
25. Messerli, B. and Ives, J.D. (1997), *Mountains of the world: a global priority*, Parthenon, New York/London.
26. Meybeck, M., Green, P. and Vörösmarty, C.J. (2001), A New Typology for Mountains and Other Relief Classes: An Application to Global Continental Water Resources and Population Distribution. *Mountain Research and Development* 21:34-45.
27. Nordic Centre for Spatial Development (2004), Mountain Areas in Europe: Analysis of Mountain Areas in EU Member States, Acceding and other European Countries, European Commission Contract No 2002.CE.16.0.AT.136, Final Report.
28. Parolo, G., Ferrarini, A. AND Rossi, G. (2009), Optimization of Tourism Impacts within Protected Areas by means of Genetic Algorithms. *Ecological Modelling* 220:1138–1147.
29. Potsiou, C. and Muller, H. (2008), Comparative Thoughts on German and Hellenic Urban Planning and Property Registration, *Technica Chronica*. Scientific Journal, Technical Chamber of Greece (TCG), I, 1-2.
30. Saaty, T.L. (1977), A Scaling Method for Priorities in Hierarchical Structures. *Journal of Mathematical Psychology*, 15, 234 – 281.
31. Serraos, K., Gianniris, E. and Zifou, M. (2005). The Greek Spatial and Urban Planning System in the European Context, Digital Review: 'Complexity and Sustainability', Edizioni Polidesign, Polytechnico di Milano.
32. Stewart, T., Janssen, R. and Herwijnen, M. (2004), A Genetic Algorithm Approach to Multiobjective Land Use Planning. *Computers & Operations Research* 31:2293–2313.
33. Sugumaran, R. and DeGroote, J. (2011), *Spatial Decision Support Systems. Principles and Practices*, CRC Press, Taylor and Francis Group, ISBN: 978-1-4200-6212-0 USA.
34. Tenerelli, P. and Carver, S. (2012), Multi-criteria, Multi-objective and Uncertainty Analysis for Agro-energy Spatial Modeling. *Applied Geography* 32: 724-736.
35. Tolidis, K., Kalogirou, C. and Dimopoulou, E. (2010), Spatial Planning in Mountainous Regions: Case Study: Prefecture of Fokida, *6th Interdisciplinary and Interuniversity Conference of NTUA: "The Integrated Development of Mountainous Regions"*, 16-19 September 2010, Metsovo.
36. White, R., Straatman, B. and Engelen, G. (2004), Planning Scenario Visualization and Assessment: A Cellular Automata based Integrated Spatial Decision Support System. In: Goodchild, M.F. and Janelle, D.G. (Eds.), *Spatially Integrated Social Science* 420–442. New York: Oxford University Press, Inc.
37. Xiao, N. (2007), Considering Diversity in Spatial Decision Support Systems, Paper presented at Geocomputation, Ireland.