A comparison of combinatory methods and GIS based MOLA (IDRISI®) for solving Multi-Objective Land use Assessment and Allocation Problems

By

Sunil Kumar Sharma

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Declaration

I declare that this thesis is based on my own research and it does not contain any material, published or submitted by another person except where duly acknowledged in the text.

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Sunil K. Sharma

Date: 12th August 2005

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Abstract

The aim of this study was to provide an informed choice among two combinatory methods and GIS based MOLA module in IDRISI® by comparing their performance in solving a hypothetical Multi-Objective Land use Assessment and Allocation (MOLAA) problem. Among the combinatory methods, Simulated Annealing and Tabu Search algorithms were chosen for study. The application of Simulated Annealing has already been demonstrated in solving a MOLAA problem but Tabu Search has not been used to a MOLAA problem before.

The Kioloa Region of New South Wales, Australia was chosen for designing a hypothetical MOLAA problem due to availability and access to the digital datasets at the Australian National University. The MOLAA problem was formulated for accomplishing six land use objectives by allocating the area to four land use types, that is, conservation, agriculture, forestry and development, using altogether 17 criteria, including 16 factors and one constraint. The criteria maps were classified in ordinal, continuous and fuzzy scale and combined by using Weighted Linear Combination to produce land use suitability models for each land use type. The ordinal and continuous land use suitability models were used in solving the problem by applying the MOLA module. In order to apply the combinatory methods, all three land use suitability models, that is, ordinal, continuous and fuzzy, were transferred to cost suitability models where the lowest cost value represented the best suitability and the highest cost value represented the lowest suitability in the interval data set. Three initial input solutions generated by the random, cheapest and greatest difference methods were used for optimising by applying both algorithms.

Both combinatory methods maximized overall land use suitability with better spatial compactness by allocating each land unit with the most suitable land use with the lowest cost. At the land use level, MOLA exhibited a bias towards land uses with lower area requirement and allocates more suitable land units to them. Though the MOLA module is highly efficient in solving large grid MOLAA problem, the combinatory methods deliver a solution close to the near-optimal solution with better compactness in an acceptable time frame. Hence, the combinatory methods have been shown to be appropriate choice to solve MOLAA problems.

The solutions were not significantly different at their mean cost functions between Simulated Annealing and Tabu Search at the appropriate parameters. Among the cost suitability models, both algorithms performed better in the fuzzy models in the large MOLAA problem. The initial input solution influenced the performance of the algorithms. The algorithms produced better results in the cheapest and greatest difference initial input solution in the medium grid MOLAA problem whereas the cost function was more improved using the random initial input solution in the large grid.

Although there is no significant difference in the mean cost functions between Simulated Annealing and Tabu Search, the previous one is found more efficient in solving large grid MOLAA problem. For the same values of compactness factors, Simulated Annealing produced more spatially compact land use allocation than Tabu Search. Thus decision makers/land use planners or consultants could obtain a better decision alternative to a land use allocation problem by applying Simulated Annealing with the recommended appropriate annealing schedule and initial input cost suitability model.

This study recommends further research in Tabu Search to find an effective attribute for a Tabu list, to be applied to a MOLAA problem.

Acronyms

ANU	The Australian National University
BRS	Bureau of Rural Sciences
CDA	Concordance-Discordance Analysis
CI	Consistency Index
CR	Consistence Ratio
CSIRO	Commonwealth Scientific and Industrial Research Organization
CSM	Climatic Suitability Map
DEM	Digital Elevation Model
DTM	Digital Terrain Model
GIS	Geographic Information System
GRASS	Geographic Resource Analysis Support System
Ha	Hectare
HO	Hierarchical optimisation
IPA	Ideal Point Analysis
JMF	Joint Membership Function
M	Metre
MCA	Multi-Criteria Analysis
MCE	Multi-Criteria Evaluation
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
MCGDM	Multi-Criteria Group Decision Making model
MODM	Multiple Objective Decision Making
MOLA	Multi-objective Land Allocation
MOLAA	Multi-objective Land use Assessment and Allocation
NP-Hard	Non-deterministic Polynomial Hard

NSW	New South Wales
NSW NPWS	New South Wales National Parks and Wildlife Service
OOC	Objectives-Oriented Comparison
OSM	Overall Suitability Map
OWC	Order Weight Combination
PCA	Principle Component Analysis
RIW	Relative Importance Weights
SA	Simulated Annealing
SDSS	Spatial Decision Support System
SR	Similarity Relation Model
SSM	Soil Suitability Map
TS	Tabu Search

Glossary

Annealing schedule	It comprises all the parameters used in Simulated Annealing such as cooling function, cooling rate, initial temperature, number of swaps per step and number of steps.
Cold swap	The swapping of land uses between two cells decreases the cost function value.
Combinatory methods	Those optimisation methods, which can solve combinatorial problems in an acceptable time frame.
Compactness function	A function used in the cost minimization function in order to enhance spatial compactness.
Cooling function	It is a mathematical rule or formula to reduce the initial control parameter or temperature in Simulated Annealing.
Cooling rate	It is the rate applied to reduce the initial control parameter or temperature in Simulated Annealing.
Cost suitability model	The models derived from land use suitability models where the lowest value represents the highest suitability and vice versa in interval scale.
Hot swap	The swapping of land uses between two cells increases the cost function value.
Initial control parameter / temperature	The initial value of temperature or control parameter used in the Simulated Annealing.
Initial input solution	The feasible solution created for optimisation, using combinatory methods.
Land characteristics	The physical attributes of land that may or may not favour a particular land use type.
Land unit	It is represented by a cell or pixel with dimension 30 m by 30 metre in a raster data set.
Land use suitability model	It implies the classification of data sets using ordinal, continuous or fuzzy methods before deriving a land use suitability map.
Land use type	It is the option to use desired use of land to achieve one or more objectives. For example, conservation, agriculture.
Metropolis criterion	A criterion that probabilistically decides whether or not to accept a move with higher cost function in Simulated Annealing.
Neighbourhood solution	A new solution generated by a small change or move in the current solution.

Simulated annealing	It is an approximation optimisation technique based on the physical process of annealing.
Swapping rate	It is the total number of swapping of land uses between two randomly selected land use units in a step.
Tabu length	It specifies the size of a Tabu list or the number of iterations for restricting a 'Tabu' move.
Tabu list	A list of specified moves or solution not accessible for specified number of iterations.
Tabu Search	It is an approximation optimization technique based on the strategy, restricting cycling of the search without improvement in the cost function and helping to avoid local minima

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Chapter 1

INTRODUCTION

1.1 Research problem

Land use is ever-changing in order to cope with the demands of population growth (Fisher *et al.*, 1996; Pieri, 1997; Theobald *et al.*, 2000; Ligtenberg *et al.*, 2001). A global estimate of land use change suggests that 1.2 billion ha. of forest/woodland have been lost since the 1700s. However, the area of agricultural land expanded by the same amount in the period (Richards, 1990). Inappropriate land use changes have been blamed for massive land degradation and associated environmental and social problems Rossiter, 1996; Nehme and Simões, 1999). These problems are more pronounced in downstream ecosystems of catchments (Allan *et al.*, 1997) because they affect water quality, biodiversity and loss of habitat (Dumanski, 1997). In Australia, land degradation has become the largest environmental problem, causing dry land salinity, acidification, contamination and vegetation degradation (ASEC, 2001). The cost of this is estimated to be about A$ 788 millions a year (Castles, 1992). The UN has recognized land degradation as a global problem affecting the goal of sustainable development and has been emphasizing the need for action at both local and national levels (WCED, 1987). To arrest further land degradation and environmental problems, the sustainable use of land resources to the extent of their potential, and not exceeding their capacity, has become a primary focus within the concept of sustainable development (van Lier, 1998).

Land use planning at the local level has emerged as a primary tool to deal with the global problem of land degradation; it partially contributes to the achievement of sustainable development through protecting natural and man-made heritage (Bruff and Wood, 2000). A major issue in sustainable use of land resources is allocation of the resources to compatible land uses with respect to land quality and the desire of the stakeholders concerned. The best possible use of land resources has become imperative in order to keep a balance between the finite limitations of land resources and the demands of the ever growing population (Kutter *et al.*, 1997).

To this end, a zoning approach has been used in land use planning to control land use but in practice, this approach has failed to cope with the new demands of land use change (Yewlett, 2001). Several methodologies have been developed to assist in the process of land use decision-making for appropriate allocation of desired land uses. This research aims to deal with some of the methodologies of land allocation for sustainable land use planning in order to ensure perpetual benefits to future generations.

Growing concern about the environment and natural resources has given sustainable use of land resource an importance in the public eye. The public is now playing an important role in sustainable land use planning, taking part in and contributing to decision-making processes. In Australia, land use planning is the primary strategy adopted to combat land degradation and other environmental problems, with the involvement of the local communities. The wide public concern over land issues is shown in the establishment of over 4,250 Landcare Groups throughout Australia to work together towards a more sustainable use of the resources (DAFF, 2004). However, land use decision-making about the allocation of available and often limited land resources for meeting social, economic and environmental objectives has become a complex issue in land use planning processes. Ultimately, the land use decision determines the social, economic and environmental conditions in a locality (Arnold, 1999).

Decisions for allocating land use are taken at various spatial scales (Bouma, 2001) by considering bio-physical, social, economic and environmental factors (Fisher *et al.*, 1996). The bio-physical attributes of the land largely determine land quality or suitability for different land uses (Ligtenberg *et al.*, 2001). However, the decisions are mainly subjected to the public (stakeholders) interest and government land use policies. It has become essential to involve the public/stakeholders in land use planning (Selman, 2001). They raise land use issues and set the objectives, the desired land uses and area requirement for each land use type.

Eastman *et al.* (1993) classified land use decision-making into two categories, single and multiple land use decisions, based on the number of land uses involved. In a problem involving a single land use or facility, the aim of any decision maker is to find the best possible location for the desired land use, or facility, from potentially suitable sites. Selection of a dumping site for nuclear waste (Openshaw *et al.*, 1989; Carver,

1991) or a research and development facility location (Tomlin and Johnston, 1988) are typical examples of a single land use decision problem. However, land use planning at landscape or regional level generally involves several land uses for achieving the wide range of land use objectives desired by the stakeholders. In this situation, land use allocation becomes a multiple land use decision problem. These multiple land uses often compete for the same land unit (Lockwood *et al.*, 1996) and conflicts among land uses become evident. This adds complexity to the land use decision-making, as the conflicting land use needs cannot be met simultaneously under limited resource conditions (Monarchi *et al.*, 1976).

The allocation of multiple and/or conflicting land uses poses a great challenge to decision-makers and planners to arrive at a consensus decision among all the stakeholders. A land use decision to allocate multiple and conflicting land uses requires reconciliation of any conflict by making a trade-off between these land uses based on their relative suitability in order to allocate the best possible land use option to each land parcel. Therefore, a solution to multiple and conflicting land use problems involves the consecutive tasks of suitability assessment of each land unit against each land use alternative and then allocating the most suitable alternative. Such a problem is appropriately described as Multi Objective Land use Assessment and Allocation (MOLAA). This problem is also known by other names such as Multi Objective Land Allocation (Eastman *et al.*, 1993), and Multi site Land Use Allocation (MLUA) (Diamond and Wright, 1989; Aerts, 2002; Aerts and Heuvelink, 2002).

A MOLAA problem is, in fact, a resource allocation problem, requiring a solution by allocating the desired land use types in a way that satisfies the area and compactness requirement. This problem may be common to all levels of spatial scales of ecosystem management. These spatial units include site level (4-200 ha), landscape level (200-4000 ha) and region level (thousands of square kilometres) (Schleusner, 1994). The problem becomes more complex with an increase in the size of the spatial scale from site (for example, at farm level with a single decision maker) to regional level (diverse landscapes with several decision makers) (Prato, 2000). However, desired solutions to MOLAA problems vary with the differences in preferences in relation to social, economic and environmental aims among the stakeholders/decision makers.

Conflicts of interest among stakeholders are also inevitable in resource allocation decision-making (Bojórquez-Tapia *et al.*, 1994; Lahdelma *et al.*, 2000; Fraser and Chisholm, 2000; Liu and Stewart, 2004; Christou *et al.*, 2004; Wester-Herber, 2004). In addition to such conflicts, the large number of land parcels or units, their spatial variability, the existence of several criteria for land evaluation and also the specified constraints such as area and shape requirements make this problem quite complex and are difficult to solve manually (Tomlin and Johnston, 1988). Therefore, adopting a comprehensive approach for land use planning that integrates social, economic and environmental factors has been emphasized for maintaining the integrity of the social and natural environments and keeping a balance with economic growth (Pieri, 1997; van Lier, 1998). Various techniques and approaches have been developed for land use suitability in order to accommodate diverse groups of stakeholders and take into account their interests in the decision-making. It is believed that these techniques are helpful for reconciling the land use conflict among the stakeholders and achieving a consensus in the multi-objective land use decision-making (Bojórquez-Tapia *et al.*, 2001).

Multi objective land use allocation has thus become an integral part of land use planning (Matthews *et al.*, 2000). The application of multiple criteria for assessing the relative suitability of single, or multiple and conflicting land uses has made the Multi-Criteria Decision Making (MCDM) approach very appealing for land use decision-making (Rietveld, 1980; Hwang and Yoon, 1981; Pereira and Duckstine, 1993; Malczewski, 1996; Malczewski *et al.*, 1997; Aerts, 2002). MCDM methods enable decision makers to use multiple and even contradictory criteria to evaluate the different options or alternatives in making a decision (Trap and Helles, 1995). These methods are discussed in chapter 2. The integration of MCDM and GIS has also proven useful for consensus decision-making among a diverse group of stakeholders (Janssen and Rietveld, 1990; Carver, 1991; Malczewski, 1996; Borórquez-Tapia et al., 2001). A list of MCDM techniques useful in solving a single or multiple land use allocation problems is given in Table 1.1. Although these methods rely on a decision rule based on Multi-Criteria Evaluation (MCE) for allocating multiple land uses, most of these methods are not able to evaluate each land unit for all land uses in order to generate an optimum or near-optimum solution to a MOLAA problem.

Table 1.1 MCDM techniques for solving single/multiple land use allocation problems

S. N.	Name of the technique	Application and limitation	Authors
1.	Multi-criteria Group Decision-making Model (AHP and Integer Linear Programming)	Evaluates feasible land use pattern using multiple criteria	(Malczewski, 1996)
2.	GIS based multivariate application	Land use suitability assessment and participatory decision-making	(Bojórquez-Tapia *et al.*, 2001)
3.	MAGISTER (Multi-criteria Analysis with GIS for Territory)	Generates a suitability map for a single land use using multiple criteria	(Joerin and Musy, 2000)
4.	MCE and GIS	Application to agricultural land use	(Janssen and Rietveld, 1990)
5.	Integration of MCE and GIS	For single land use allocation based on MCE	(Carver, 1991)
6.	Multi-objective Programming Modelling	For single land use allocation	(Diamond and Wright, 1989)
8.	Integer Linear Programming	Multiple land use allocation for small number of land units	(Aerts, 2002)

An optimum solution to a MOLAA problem may be achieved by allocating each land parcel (unit) with the best possible land use, meeting all specified constraints (area or shape requirement). The solution will maximize overall land use suitability. However, the optimum solution lies within the innumerable possible combinations of the land units and land use alternatives and constraints (Diamond and Wright, 1989). Computationally, it is not feasible to search for every possible combination of decision variables (land unit and land uses) and constraints (area or shape requirement) to find the optimum solution in a reasonable amount of time, using either systematic or mathematical optimisation techniques within the MCDM. Many real world problems are of this nature and have been classified as combinatorial problems (van Laarhoven and Aarts, 1987; Aarts and Korst, 1989; Voudouris, 1997).

One group of optimisation techniques has been successful in delivering sub-optimal solutions to combinatorial problems in an acceptable time. These techniques trade off the optimality of the solution with computational time and deliver a near-optimal solution in an acceptable time frame (van Laarhoven and Aarts, 1987). They are collectively called approximation algorithms or heuristic methods (Aarts and Korst, 1989). These methods are finding wide application in many fields because of their simplicity and their ability to solve complicated problems (Youssef *et al.*, 2001).

Three famous approximation optimisation techniques that have proven useful for generating an acceptable solution to many real world combinatorial problems are Simulated Annealing, Genetic Algorithm and Tabu Search (van Laarhoven and Aarts, 1987). Simulated Annealing has been successfully applied in solving a multi-objective land use allocation problem in a post-mining restoration site in As Pontes, Spain using raster data (Aerts, 2002). The algorithm delivered a solution by minimizing the cost function, allocating each land unit with the best possible land use, that is, with the lowest development cost. The development cost model was derived by using two land attributes applying different factors for these land uses (Aerts, 2002; Aerts and Heuvelink, 2002). Nevertheless, this algorithm has not been compared with other combinatorial methods so far. Therefore, the comparative performance of Simulated Annealing and the quality of the solution are untested. From an application viewpoint, a comparison of Simulated Annealing with one of the combinatorial methods in solving the same MOLAA problem may provide users with an informed choice of these methods, based on the quality of the solution and the performance of the algorithm.

Although Genetic Algorithms have been used for MOLAA problems at the farm level, they have not been applied at larger scales, that is, landscape or regional scale. Matthews *et al.* (2000) noted that use of raster data causes computational inefficiency of the algorithm. Tabu Search is not yet tested for a MOLAA problem; however, it has successfully delivered an efficient and effective solution to similar combinatorial problems. Based on its simplicity and on its demonstrated applicability to similar problems using raster data, Tabu Search algorithm has been found to be appropriate for solving the same MOLAA problem in this research in order to compare its solution with that of Simulated Annealing.

In a GIS environment, a decision support module capable of solving a MOLAA problem has been developed based on decision heuristics and used for single land use allocation (Eastman *et al.*, 1993). This module is available in IDRISI® GIS software and is called MOLA (Multi Objective Land Allocation). MOLA allocates land units among the desired land uses, satisfying the area requirement and users' preference. However, the quality of the solution obtained by this method is not known, as the solution to the same MOLAA problem has not been compared with other methods yet.

The main goal of this study is to compare the performance of two combinatory methods, that is, Simulated Annealing and Tabu Search and the MOLA module in IDRISI® in order to provide an informed choice among these methods in solving a multi-objective land use allocation problem. In the research design, it was planned to test the application of both combinatory methods in a hypothetical MOLAA problem in the Kioloa region in New South Wales (Australia). The performance of these methods were assessed based on the improvement in the cost function, spatial compactness, computation time and input model requirements.

In land use allocation, a larger patch of the same land use is more desirable for many reasons than a scattered distribution of one land use (Aerts, 2002). For example, a spatially compact reserve area is preferred because of low management cost (McDonell *et al.*, 2002). Hence, a compactness function has been incorporated in both combinatorial methods to enhance the spatial compactness in land use allocation. The solutions found by applying compactness function were compared between these two methods.

1.2 Research objectives

The main objective of the research is to compare the performance of Simulated Annealing, Tabu Search and the MOLA module in IDRISI® by applying them to solve a Multi Objective Land use Assessment and Allocation (MOLAA) problem. The aim is to provide an informed choice among these methods to the users. These methods treat each cell of the raster dataset as a land unit and yield a solution by searching for the best possible combination of all the decision variables (land use types and land units). The following parameters will be assessed in the output solution for comparing the performance of these methods:

- improvement (minimization) of the cost functions;
- spatial compactness in terms of number of patches for the different land uses;
- enhancement of spatial compactness after incorporating compactness function in Simulated Annealing and Tabu Search algorithms.
- computational (run) time taken to deliver the solution;

This research also aims to find an appropriate combination of parameters for Simulated Annealing and Tabu Search, and a suitable initial input solution and cost suitability model in order to apply these algorithms in solving a MOLAA problem. The algorithms are applied with different combination of settings of parameters to three different initial input solutions derived from three cost suitability models.

1.3 Implications of the research

Land use planners or decision makers facing multiple land use allocation problems during the land use planning process may use these methods as a decision support tool for generating a solution to a specific MOLAA problem. The selection of one decision support tool is not an easy task and the users should employ a conscious logic in making their choice (Lahdelma *et al.*, 2000).

The users would ideally be interested in obtaining the most comprehensive solution, in the least computational time, with simple data input. However, the solutions generated by these methods may not be the same. To be able to decide on the most appropriate method, the users (decision makers/planners) should know have some knowledge of the methods applicable to the MOLAA problem, as well as the input requirements and the quality of the solutions reached from these methods. This research aims to address these multiple interests of users; thus, the implications of the research can be broadly stated as follows.

- To allow the characterization of three methods for different circumstances, data and intentions;
- To provide users of the MOLAA with information necessary to make informed choices among these methods.

Decision support tools have been developed to facilitate decision-making by providing alternative solutions to a problem. However, how good is that solution? The stakeholders may judge the quality of the solution by assessing whether or not their values/interests have been truly reflected in the solution. The equity or fairness of the decision-making process will enhance the effectiveness and acceptability of the decision (Hunt and Haider, 2001). It is necessary for the decision makers to ensure 'procedural fairness' of the decision support tool in order to bring them to a consensus decision. Hence the implication of this research will also on the 'procedural fairness' of these methods by assessing their bias towards a particular land use.

1.4 Background concepts

1.4.1 Land and land use

'Land' has a very wide meaning and scope in geo-political, socio-cultural and economic terms (Hamblin, 2001). Hence, land cannot be defined in an easy way. However, every human can conceive of it in its physical identity. In economic terms, it is the wealth and capital input for production activities. In a geo-technical context, land is the outer crust of the earth and also includes inland water bodies, estuaries and coastal areas. It has a permanent geographical location covering a finite area and can be described by its physical characteristics such as topography, soil and subsurface structure and composition (Davis, 1976). These characteristics are used for classifying land categories and are also taken into account for land use planning.

'Land use' is defined as all kinds of human intervention in order to derive goods and services from land and can be categorized into three groups, *production* (agriculture, forestry, grazing, mining), *services* (conservation or ecological services, water production, recreational) and *infrastructure development* (housing, roads, bridges) (Vink, 1975). According to Eastman *et al.* (1993) land uses can be both complementary and conflicting. Complementary land uses can co-exist together spatially as well as temporally whereas conflicting land uses cannot.

There have been attempts to classify land uses into coherent groups by generalizing detailed observations. Some of the major land use classifications include the World Land Use Survey (early 1930s), Second Land Utilization Survey (late 1960s), The United States Geological Survey and The National Land Use Classification (Rhind and Hudson, 1980). These broad schemes have attempted to provide land use classification for a particular purpose, and vary widely in terms of the extensiveness of the area, the map scales or source of data (for example remote sensing imagery). None of these classifications coincide in terms of the number of land use classes and their description. In Australia, land uses have most recently been classified into nine classes based on the major use of land and the level of anthropogenic intervention (Stewart, 2001).

Land cover refers to the physical description in terms of the nature of the surface and the types of vegetation covering it (Gregorio and Jansen, 1998). 'Land use' is described strictly in terms of human use, for example land cover might be broadleaf forest, but land use might also be conservation reserve. This research focuses on land use allocation for different uses of land as determined by human beings.

1.4.2 Land valuation and land evaluation

'Land valuation' is the economic gain from the goods and services supported by the land (Davis, 1976; Hanink and Cromley, 1998). Some values attached to land like recreational, environmental, aesthetic and social values are difficult to measure in monetary terms. However, the pricing of these values can be accomplished by some indirect methods like hedonic valuation, travel cost and household production function (McConnel, 1993) and contingent valuation (Lockwood *et al.*, 1996).

'Land evaluation' is the quantitative or qualitative assessment process for assessing potential use of land by using some land attributes (Rossiter, 1996). According to the FAO, land evaluation is a part of the land use planning process used to assess the performance of land in terms of economic gain, social impacts and environmental consequences of present land use (FAO, 1976). FAO has developed a *Land Evaluation Framework* or *FAO Framework* in order to standardize the methods and reconcile different methods used by different countries (Davidson, 1992). The main aim of land evaluation is to grade land for particular land uses, analysing the social, economic and environmental implications and finally to identify the suitability of the land for one or more land uses.

'Land evaluation' is, therefore, a thorough investigation of all the benefits and all the impacts arising from the potential land use. FAO has published guidelines for several land use types including rain fed agriculture (FAO, 1983), forestry (FAO, 1984), irrigated agriculture (FAO, 1985), and extensive grazing (FAO, 1991). Initially, land evaluation approaches focussed solely on estimating agricultural productivity of land by using soil parameters for land use decision-making (Bacic *et al.*, 2003). There have been several computer based models available for land evaluation, suitable for specific land use types or land qualities or climates (Wood and Dent, 1983; Rossiter, 1990; De la Rosa *et al.*, 1992; Rossiter and Van Wambeke, 1995; Fisher *et al.*, 1998).

1.4.3 Land capability and land suitability

The terms 'land capability' and 'land suitability' seem to be quite similar and are often used interchangeably. Vink (1975) defined these terms as the ability of the land to offer a certain specified land use as determined by the socio-cultural and economic conditions. Davis (1976) has defined land capability in two domains. First, he defined land capability in terms of land itself, as a measure of a combination of inherent physical attributes of the land, the climate and the vegetation. Second, he attempted to classify land capability based on specific land uses such as agriculture, forestry and engineering through assessing the extent of physical limitations, management and conservation requirements. This definition combines both the land's physical characteristics and climatic information and also accounts for the limitations imposed by these physical attributes.

The initial intention was to classify land into different capability classes for agricultural land use. The US Soil Conservation Service had first classified land capability into eight capability classes, four sub-classes and several units based on soil survey data (Rhind and Hudson, 1980). Though this land capability classification was intended to be used in making agricultural decisions, it was applied to all planning purposes (Steiner, 1983). Subsequently, other countries like Canada and Britain developed their own land capability classification, in order to suit land use planning and management (Davidson, 1992). The main aim of these classifications was to facilitate land use planning through categorizing land into different classes or subclasses based on land characteristics, considering the factors and the constraints that favour or limit a land use type.

However, land use decisions based merely on the land's physical attributes were soon realized to be inadequate to satisfy the growing environmental consciousness and economic thinking of the public on land use issues (Bojórquez-Tapia *et al.*, 1994). Planners or decision makers responded to it by including social, economic and environmental implications of proposed land uses besides the land's physical capability. A comprehensive evaluation of land units for particular land uses has thus become essential for assessing their relative suitability for different land uses.

Evaluation of land in terms of its physical characteristics (land capability) and the social, economic and environmental implications of proposed land uses are included in the term land suitability (Davidson, 1992). Steiner (1983) defined land suitability as fitness of a land unit for a particular land use. McHarg (1969) used land suitability as the presence of all the favourable parameters in the absence of the constraints for a particular land use, making the land 'intrinsically suitable' for that particular use.

Land suitability measures the condition or state of land relative to a particular land use indicating land quality (Dumanski, 1997). Land quality signifies the condition of land resources relative to different land uses like agriculture, conservation and forestry (Pieri *et al.*, 1995). It is measured by the suitability of the land for a specific use and can be enhanced or degraded by land use type and management practices (Dumanski, 1997). A land suitability assessment provides a rating for each land unit with respect to its suitability for each land use, to enable the planners to make an objective decision based on the relative suitability values of all potential land uses; suitability has been categorized into actual or current suitability and potential land suitability (Brinkman and Smyth, 1973; Vink, 1975; Hall *et al.*, 1992). Current or actual land suitability implies suitability of land in its present condition, that is, without improving or changing the land conditions. Potential land suitability takes into account land suitability that is feasible only after some major land improvement requiring a major capital investment has taken place.

Different approaches have been adopted for analysing land suitability for the purpose of land use planning. The Dutch method is a land capability classification focused solely on soil characteristics, thus its approach is mainly appropriate for land suitability assessment for arable and grassland uses. McHarg (1969) proposed a method for land suitability assessment combining the characteristics of land use, natural parameters and their compatibility. Within agricultural land use, the land's suitability for different crops has been extensively researched to aid decision-making by providing the best crop type for each land unit (Johnson *et al.*, 1994; Ahamed *et al.*, 2000; Ceballos-Silva and López-Blanco, 2003).

This research therefore assesses the relative suitability of each land unit for all potential land uses, taking into consideration not only the land's attributes in relation to each land use type, but also including appropriate spatial or non-spatial, social, economic and environmental parameters. The inclusion of other evaluation criteria besides the land's attributes implies the suitability of the land unit for the prescribed land use rather than land capability. Hence, the term 'land suitability' is considered to be more appropriate for this research. These evaluation criteria are combined following a rule of combination as decided by the decision makers and the stakeholders. This research applies different approaches to land suitability assessment and the solutions will be compared. The details of these approaches will be discussed in Chapters 2 and 5.

1.4.4 Land use objectives and conflict

Land serves a wide range of objectives that may be social, cultural, economic or environmental. These objectives are the key to making decisions on the evaluation criteria (Huddleston, 2002) and also land use types for ultimate land use allocation for either single or multiple land use types. In the case of a single land use, a decision-making problem may arise when there are several land parcels or units suitable for the specified land use and only one site has to be chosen. It requires an assessment of all potential land parcels and finding the best, most suitable site for the desired land use. This problem has been called a 'single facility location problem' or 'facility siting problem' (Tomlin and Johnston, 1988; Carver, 1991).

A 'Multiple Land Use problem' requires the allocation of the most suitable sites for each land use. However, the multiple land uses must be further segregated into compatible or non-compatible land uses depending on whether they can coexist or not (Eastman *et al.*, 1993). Compatible land uses can be allocated to the same land parcel at the same time. These may be complementary or coexisting land uses. During the designing of the land use problem, compatible land uses can be merged together into one land use type and allocated to the same unit of land.

Incompatible land uses cannot be allocated to the same land unit at the same time. Mostly, exhaustive or consumptive land uses are incompatible and compete for the same land parcels (Miller and Carter, 1979). It means that land can be assigned for only one land use at a time, not for both, for example, timber production and nature conservation. These are also called conflicting land uses. Whenever there are different groups of people or stakeholders interested in incompatible land use objectives this gives rise to a conflict over land use (Bojórquez-Tapia *et al.*, 1994; Dale *et al.*, 2000). Such conflict is resolved by "consensual land use decision making" through involving all the concerned stakeholders to reach a common point (Bojórquez-Tapia *et al.*, 1994). This research focuses on three different methods (two combinatory methods and a GIS based MOLA module) which can be applied within the framework of a decision support system for a consensus decision among stakeholders on a multiple and conflicting land use allocation problem.

1.4.5 Land use planning and land use allocation

FAO (1976) defined land use planning as a procedure to identify the most suitable land use from the available land use options, taking into consideration the social and economic conditions and land and water capabilities. However, the involvement of interest groups or stakeholders in land use planning is not made explicit in this definition. Recently, the Sahtu Land Use Planning Board, Canada (2003) defined land use planning as identifying guiding principles for using land and its resources for the social, cultural and economic interests of all the stakeholders. In the Northern Territory Government's (2003: 1) point of view, "land use planning is the process whereby the Government works with the community to establish agreements on how land suitable for development can be identified, serviced, built upon and used for social economic purposes in environmentally sustainable ways".

One of the main goals of land use planning is to achieve economic efficiency, social equity and sustainability of the resource. It is necessary for land use planning to guide decision-making on land use (FAO, 1976). It aims to harmonize economic development with environmental sustainability to fulfil the social, cultural and economic aspirations of the people. Land use planning has become an indispensable part of sustainable development throughout the world to ensure that current as well as future, land use changes will not threaten or damage the environmental sustainability of the region.

During the process of land use planning, the decision about the land use is the main focus of planners or decision makers and that determines the comprehensiveness of the land use planning to achieve its goal. The suitability of the land unit for more than one non-compatible land use, and also the conflicting interests and preferences of the stakeholders (Campbell *et al.*, 2000), add complexity and make it impossible to select the best land use option for all the land units. This is a decision-making problem encountered in every land use planning process and may be called the "land use allocation problem". This problem can be solved by seeking a compromise solution through assigning a best possible land use to each land unit, and thereby maximizing overall suitability of the land use.

1.5 Organization of the thesis

This thesis focuses on two combinatory methods and one GIS based MOLA module in solving a MOLAA problem and compares their performance in order to provide an informed choice among these methods based on the run time, optimum result and the input required from prospective users (planners or decision makers). The thesis is divided into ten chapters. A brief description of each chapter is presented here:

Chapter 1: Introduction

This chapter discusses the issues and problems of land use planning/decision-making and formulates a research problem for comparing two combinatory methods and a GIS based MOLA module in IDRISI® software in solving a MOLAA problem. This chapter also presents the research objective, implications and some background concepts in order to clarify relevant terminology in the context of this research.

Chapter 2: Approaches of multi-objective land use decision-making

A framework in the context of land use decision-making is presented in this chapter. Different techniques of land suitability assessment and decision support tools focussing on various methods of the Multi-Criteria Decision Making (MCDM) are discussed based on the available literature.

Chapter 3: Methods for multi-objective land use allocation

The theoretical principles of combinatory methods and Simulated Annealing and Tabu Search algorithm are elucidated here. This chapter also describes the MOLA module in IDRISI®.

Chapter 4: Research framework and study site

The framework for this research and a brief note on each step in the framework are provided in this chapter. The study site and the available digital datasets are also discussed.

Chapter 5: Methodology

A detailed methodology is presented in this chapter. It describes the generation of land use suitability models using three different quantitative scales, cost suitability models and three initial input models using the random, cheapest and greatest difference methods. This chapter also specifies the parameters for Simulated Annealing and Tabu Search.

Chapter 6: Result I – Applying MOLA in solving a hypothetical MOLAA problem

This chapter presents the results obtained after applying the MOLA module in solving a hypothetical MOLAA problem in the Kioloa region, NSW. The ordinal and continuous land use suitability models are used and the results are analysed in the MOLAA problem in a small grid.

Chapter 7: Result II – Applying Simulated Annealing to the hypothetical MOLAA problem

The results of applying Simulated Annealing to the hypothetical MOLAA problem using the ordinal, continuous and fuzzy cost suitability models are presented. Different combinations of annealing schedules are applied to three different initial input solutions produced by the random, cheapest and greatest difference methods. An appropriate annealing schedule and initial input model will be sought for applying Simulated Annealing to a MOLAA problem.

Chapter 8: Result III – Applying Tabu Search to the hypothetical MOLAA problem

This chapter presents the results of applying Tabu Search to the same hypothetical MOLAA problem using the same cost suitability models. Different parameters and initial input solutions are used for finding the best parameter combinations and input solution for applying Tabu Search to a MOLAA problem.

Chapter 9: Result IV – Comparing the combinatory methods and MOLA module in solving the hypothetical MOLAA problem

The solutions obtained by applying Simulated Annealing, Tabu Search and the MOLA module to the same hypothetical MOLAA problem are compared in this chapter. The quality of the solution and efficiency of these methods are compared and assessed in solving a MOLAA problem.

Chapter 10: Conclusions

This chapter presents the conclusions reached in relation to this research. The conclusions are drawn on the appropriateness of application of each of these methods in solving a MOLAA problem using the different input models chosen. Recommendations are also made about future research.

1.6 Papers from this thesis

Sharma S. K. and Lees B. G., 2004 *A comparison of simulated annealing and GIS – based MOLA for solving Multi-Objective Land use Assessment and Allocation Problem.* Paper presented at XVII International Conference on Multi-Criteria Decision Making, 6-11 Aug. 2004, Whistler, British Colombia, Canada.

Sharma, S. K., 2004 *Spatial decision support using Simulated Annealing*, Paper presented at the Fifth Australasian Postgraduate Workshop on GISc, Social and Environmental Modelling, 1-6 Feb. 2004, Kioloa, New South Wales, Australia.

Sharma S. K., Lees B. G., M. J. Hill and Leahy, S., 2005, January, *Implementing Simulated Annealing for solving a Multi-objective Land use Assessment and Allocation problem.* International Journal of Geographic Information Science (Paper on review).

Chapter 2

APPROACHES TO MULTI-OBJECTIVE LAND USE DECISION-MAKING

2.1 Introduction

Multi-Objective Land use Assessment and Allocation (MOLAA) is a typical example of a land use decision-making problem. In this problem, the prime aim of the decision maker is to reach a consensus decision on land use allocation among stakeholders through maximizing the overall land use suitability of multiple and often conflicting land uses. In order to approach a MOLAA problem at landscape or regional scale, it is imperative for the decision makers to follow a framework of land use decision-making which enables them to achieve the above aim. This chapter will briefly explain the concept of decision-making in the context of land use, present an analytical framework and describe each element of the framework. Various approaches and techniques have also been developed to deal with the complexity of land use decision-making. This chapter will thus also evaluate some of these approaches and techniques being used for land use decision-making.

2.2 Land use decision-making

Decision-making is a situation that arises due to the availability of choices or options to address a problem. Hwang *et al.* (1979) defined decision-making as a process of choosing appropriate option(s) to accomplish desired objective(s) from the potential alternatives. To Eastman *et al.* (1993), it is a selection from a set of available options, actions or expectations. He called these alternatives the "decision frame" and referred to the area where the decision frame is applied as the "candidate set". The set belonging to each member of a decision frame is called a "decision set". In decision-making one has to decide which decision frame applies to each of the candidate sets. The above definitions by Hwang *et al.* (1979) and Eastman *et al.* (1993) imply that land use decision-making is a process of matching available land parcels with appropriate land uses for achieving the desired social, economic and environmental objectives.

Land use decision making with several stakeholders or decision makers has become a very complex task because of conflicts of interest regarding the land use (Mills and Clark, 2001). This difficulty may be attributed to differences in socio-economic aims among the stakeholders (Bojórquez-Tapia *et al.*, 2001). Land itself adds complexity to the decision-making process, as not all land is suitable for all land uses, rather it offers varying relative suitability for different land uses, depending upon the land's characteristics together with the land use requirement (Hall *et al.*, 1992). A land unit may be suitable for more than one non-compatible land use, all of which could not co-exist on the same land unit in the same time and space (Eastman *et al.*, 1993). In addition, the immobility and finiteness of the land add further limitations to the land use decision-making process.

Land use decision-making for a single land use is relatively easy and straightforward and can be accomplished by comparing the suitability values of the entire available, potential land parcels. However, the decisions become more complex and challenging with the involvement of multiple land uses due to the involvement of stakeholders having social, economic and political differences (Brill *et al.*, 1982). Davis (1976) has ascribed the complexity of land use decision-making to divided land ownership, and multiple authorities among the federal and state governments, private landowners and interest groups. However, the severity of the problem may be attributed to the sensitivity of the area, its social, economic and environmental importance and the extent of the area. At farm level, land use decisions have been found to be influenced by the land holding size and also the economic status of the farmer (Ravnborg and Rubiano, 2001). As in other domains, land use decision-making is also characterized by risk and uncertainty due to the incompleteness and lack of accuracy of the datasets (Aerts, 2002). In summary, land use decision-making problems tend to be case-specific and are governed by the extent (size), data sources and their accuracy, heterogeneity among the stakeholders and their land use interests and also the bio-physical characteristics of the land itself.

The aim of land use decision-making is to come to a consensus decision on land use allocation among all the stakeholders through maximizing the land use suitability of multiple and conflicting land uses. Hence, it has become an integral part of physical land use planning, to ensure compatibility between the land resources and land uses for ensuring sustainable development. In a comprehensive land use planning process, physical planning follows "land development" and "land management" aiming at improving the physical condition of the land and the sustainable use of land, respectively (van Lier, 1998). A general decision-making process includes the following steps: problem identification; possible alternatives; choice of criteria; evaluation of alternatives; and selection of the alternative(s) (Baird, 1989). In the context of land use decision-making, definitive answers to the following questions are sought: "What are the land use objectives and types?" "What is the best possible land use option for each land parcel?" or "Where is the best land parcel for a particular land use?"

2.3 A framework for land use decision-making

Land use decision-making is a process which involves single or multiple land use allocation problems, taking into consideration spatial, temporal and environmental issues. It has become a subject of public concern and needs to incorporate all the social, economic and environmental objectives of all the concerned public, institutions or agencies for rational and consensus decision-making (Miller *et al.*, 1978; Liu and Stewart, 2004). The framework chosen for decision-making differs with the issues, however; a general framework for land use decision-making should contain several elements. Each of the elements is described briefly in the following sections.

2.3.1 Problem Structuring

2.3.1.1 Stakeholders and decision makers

Land use decision-making over public land is no longer a single person's decision or even a top-down approach (Williams *et al.*, 1998). Securing the involvement of the public or actors in any development effort has become a prerequisite for the smooth implementation of a project delivering its objectives (Friedmann and Kuester, 1994; Pieri, 1997; Ligtenberg *et al.*, 2001). FAO has emphasized the need for adopting a participatory approach through the active involvement of stakeholders in land use planning/decision-making (FAO, 1993; Kutter *et al.*, 1997) in order to provide them with the opportunity to participate and to speak out about their land use interest or objectives. In Mexico, the law enforces the participation of all stakeholders in land use planning (Bojórquez-Tapia *et al.*, 2001). In Canada, the Commission on Resources and Environment has adopted a shared decision-making approach as a primary strategy for securing public involvement in the land use planning process (Williams *et al.*, 1998;

Duffy *et al.*, 1998). This approach recognizes an equal share among the decision makers – those who have got the right to make decisions and the stakeholders - those people who will be affected by the decisions, in the land use decision-making process.

In land use decision-making, 'stakeholders' can be identified as an individual, community, groups or organization that have some interest in land use of a specified area (Hurni, 1997). The stakeholders are now considered an 'integral part' of the decision-making framework (Theobald and Hobbs, 2002). For example, ten major stakeholders have been identified for land use decision-making in Michigan, USA (MLULC, 2002). At the landscape or regional level, multi-level stakeholders are involved and are usually heterogeneous socially, economically and politically. Stakeholders having different socio-economic and environmental aims may intend to use the same parcel of land for different land uses (Muchena and van der Bliek, 1997). They will have different preferences regarding the significance of criteria used for assessing different alternatives for decision-making (Malczewski, 1996). These differences can be attributed to conflicting interests or preferences among them regarding use of a particular land parcel (Bojórquez-Tapia *et al.*, 1994; Zander and Kächele, 1999). However, the involvement of stakeholders in the decision-making process can be beneficial in two ways. First, they feel ownership of the decision and second, they commit themselves to a positive role in the implementation of the decision.

The prime role of a decision maker is to facilitate the decision-making process through encouraging participation of all the stakeholders and to strive for a consensus decision on land use issues. The land use decision-making process becomes more complicated with the involvement of conflicting interests among the stakeholders and thus, requires a rigorous approach and a appropriate tool to reach consensus decisions on the issues.

Several approaches for involving stakeholders in land use decision-making have been developed in order to incorporate their interests and preferences for achieving consensus (Bojórquez-Tapia *et al.*, 1994; Malczewski *et al.*, 1997; Moote *et al.*, 1997; Aerts, 2002; Skogen, 2003). In this research, the hypothetical problem will not use real stakeholders; rather, it relies on expert knowledge and the literature on land use policy to decide on different land use issues.

2.3.1.2 Land use objectives and land use (type)

Eastman *et al.* (1993) did not distinguish between **land use objectives** and **land use types** in the context of land use decision-making. However, I find these two to be clearly different, although complementary to each other. The land use objective constitutes every single need of the stakeholders and may encompass social, economic and environmental purposes. The identification of a land use objective is the foundation for defining relevant land use types for an area. In an allocation problem in a residential area, the primary objectives include having access to services like water and electricity, requiring minimum cost for construction and minimum damage to the environment (Gilbert *et al.*, 1985). The stakeholders may come up with several further objectives, like to protect native wildlife and vegetation, maximize timber production and recreation, protect the soil and so on. These land use objectives clearly incorporate conservation, production forestry and recreation as land use types. The remaining objective of protecting the soil may be achieved by setting a criterion which restricts forestry operations or agricultural use on sloping lands. These objectives are, therefore, the prerequisite for formulating the decision rules for determining suitability of different land use alternatives or types (Eastman *et al.*, 1993).

Land use (type) simply implies the primary use of land for social, economic or environmental objectives or any combination of these objectives. The major land use types often considered in land use decision-making include conservation, agriculture, forestry and urban areas. The choice among the different land uses is determined by human needs or the purpose to be met from the utilization of a particular land parcel. Four land use types, that is, conservation, agriculture, forestry and residential, were identified for achieving six land use objectives concerning social, economic and environmental issues in designing a hypothetical land use decision-making problem. These land use objectives and land use types are elaborated in Chapter 5.

2.3.1.3 Land use evaluation criteria

Land use evaluation criteria are simply the basis for measuring the degree of suitability of a parcel of land for different land use types and determining the appropriateness of the land use allocation (Gilbert *et al.*, 1985). Eastman *et al.* (1993) categorized evaluation criteria into **constraints** and **factors**. Constraints are generally the conditions which tend to restrict the particular use of this land, making the land parcel unsuitable.

For example, flood-prone and fire-hazardous areas may be regarded as constraints on residential use and therefore land parcels prone to these conditions will be excluded from suitability consideration. Factors are those land attributes which contribute to the relative suitability of the land parcel or unit for a particular land use, as determined by the attribute classes. The factors are further classified into attribute classes using qualitative and quantitative measures, reflecting the relative suitability of each class for a specified land use (Basnet *et al.*, 2002).

A single criterion may not be adequate for evaluating the suitability of a land use alternative. Therefore, decisions regarding all real-world problems should be made using several criteria (Carver, 1991). However, there are no guidelines on how many, and which, criteria are appropriate for assessing land use suitability. The number and types of criteria may be determined by the data available and also the resources available, for example time, money and the ability to collect new information. However, the criteria should encompass social, cultural and economic as well as environmental needs of people (Osinski *et al.*, 2003).

In this research, altogether 17 evaluation criteria including 16 factors and one constraint were chosen for four land use types in a hypothetical problem. These criteria will be discussed in Chapter 5. The multiple evaluation criteria should be combined to obtain an aggregate of suitability values for comparing all decision alternatives. The process of combining selected criteria is called a decision rule (Eastman *et al.*, 1993) and will be discussed in the next Section 2.3.2.

2.3.1.4 Spatial criteria in land use allocation

The spatial criteria in land use allocation may include area, compactness and adjacency requirement. In a multi-objective land use allocation problem, the area requirement for each land use type is a primary decision to be made in order to arrive at an exact allocation of area for each land use to derive all the land use objectives desired by the stakeholders and decision makers/planners.

Compactness is a spatial characteristic (Knight, 2005) and is used in as a relative term to describe pattern and distribution of shape of spatial unit such as land unit. A relatively compact solution is highly desirable in a land use allocation problem (Diamond and Wright, 1989; Aerts *et al.*, 2003). In a multi-objective land use allocation problem, the spatial compactness can be enhanced by allocating adjoining land units with the same land use. This was accomplished by incorporating a compactness function in a decision support tool (McDonnell *et al.*, 2002; Aerts and Heuvelink, 2002). Several techniques have been developed to measure compactness, each with its own scope and limitations (Knight, 2005). This research uses the number of patches at land use level as a measure of spatial compactness and is obtained by using FRAGSTAT® under the eight or four neighbours rule.

An adjacency criterion is also often used in harvesting scheduling in forest planning in order to avoid or restrict excessive felling in an area (Lockwood, 1993; Boston and Bettinger, 1999). Adding the adjacency criterion to the multi-objective land use allocation makes the problem very complex. Hence, only spatial compactness and area requirement are taken into account in solving the multi-objective land use allocation problem in this study.

2.3.2 Land use suitability assessment approaches

Land use suitability assessment is used to evaluate the degree of appropriateness of a land unit for a particular land use. The isolated suitability map generated for each criterion may be useful for viewing and locating areas that are more or less suitable for that land use. Therefore, it may not be enough for decision-making where several evaluation criteria and preferences are to be taken into account. Since the 1960s there have been continual efforts to provide an acceptable framework and methodology for land suitability assessment (Davis, 1976), through which different approaches have been evolved. A simplified framework for land suitability assessment is given in Figure 2.1. The framework includes a land use type to accomplish one or more land use objectives or goals at the top of the hierarchy. Relevant criteria and classification of the attributes within physical (environmental), social and economic domains are fundamental to defining the degree of suitability of different attribute classes for the land use. A combined map of all these criteria indicates the relative suitability of each land parcel in qualitative or quantitative terms.

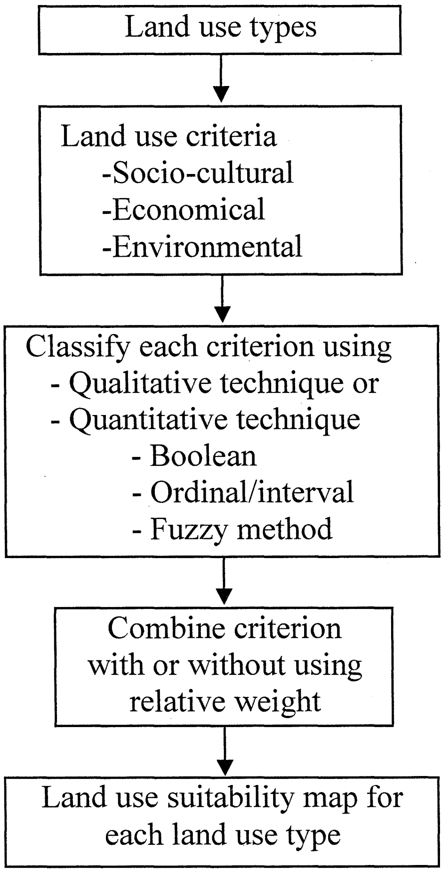


Figure 2.1 A general framework for land use suitability assessment

The approaches to land suitability assessment may be classified into qualitative and quantitative techniques based on the representation of the criterion attributes and the rule of combination. Qualitative techniques include a preliminary way of describing land suitability by specifying suitability along a continuum, as "highly suitable", "moderately suitable", "suitable" and "unsuitable". Some examples of this technique are the Gestalt method (Hopkins, 1977), light table method (McHarg, 1969) and decision tree method (Bydekerke *et al.*, 1998). These qualitative methods may be useful in multi-objective land use decision-making by transferring the qualitative values to quantitative values to serve the purpose of comparing the degree of suitability of each land use for every land unit, in order to optimise a cost function.

Quantitative techniques use either ordinal, interval or ratio scales to represent the attributes of a criterion signifying the relative degree of suitability. Various techniques are available for combining multiple attribute values to derive final or overall suitability. The realization of the difference in relative importance of different bio-physical and economic criteria to various land uses has lead to the development of the weighting method. This aims to assign variable weights, based on their significance, to the land use objective by giving higher weights to the relatively more important factors. On these grounds, the quantitative techniques of land suitability assessment may be categorised into two groups:

1) Without considering factor weight and;

2) With factor weight.

Some of the techniques associated with each group are discussed below. However, those approaches based on Boolean logic do not distinguish among varying degrees of suitability due to the differences in the attribute classes of a criterion. Every land parcel is assessed for a desired land use, whether it meets the land use requirement or not, and is assigned '1' for suitable (unconstrained) areas and '0' for unsuitable (constrained) areas. This logic may work for assessing suitability for a single land use but is not appropriate for multiple land use allocation. Therefore, land suitability approaches based on Boolean logic are not discussed further here.

2.3.2.1 Without considering factor weight

1. Ordinal combination method

The attributes or classes of each factor are classified on an ordinal scale, for example from 1 to 5, representing highly suitable, suitable, moderately suitable, fairly suitable and unsuitable classes, respectively or in the reverse order. The suitability model is generated by combining all the factor maps by using a simple linear additive procedure (Equation 2.1). This operation can easily be carried out using any GIS software employing simple Map algebra. This method is the same as McHarg's Light Table technique; however, the values are represented on an ordinal scale instead of in grey tones to signify the relative importance of the factors.

$$S = \sum_{i=1}^{i=n} x_i \qquad \text{Equation 2.1}$$

Where S is the suitability value and x_i is the value for factor i.

A System for Selecting Suitable Sites (ASSESS) is a GIS based decision support system which uses an ordinal combination method for assessing land use suitability (BRS, 2003). The final suitability map is generated based on the factor attributes categorized into the suitability rating classes, for example 1 to 5, by users. It has proven a useful decision support tool for several Multi-Criteria Decision Analysis (MCDA) applications

(Hill *et al.*, 2005). These include: land use suitability for low-level radioactive waste material (Veitch, 1997); agricultural suitability in the Murray Darling Basin (Bui, 1999); and assessing catchment conditions in intensive land use zones of Australia (Walker and Veitch, 2001).

The ordinal combination method provides an overall rating of suitability by combining all the factor values in the ordinal scale. In doing so, a lower value for one factor is compensated for by the higher value of another factor and generates the same suitability values for two extreme values. However, while these suitability values are the same mathematically, this may not hold true in the real world (Lees, 2004).

2.3.2.2 Taking account of factor weight

1. The FAO method

FAO's approach quantifies land suitability based on the relative adaptive value assigned to the relevant land attributes and their significance for the intended land use (FAO, 1976). The relative significance of each land attribute in regard to the particular land use is taken into account by multiplying the attribute value with an integer value between 1 and 5. Those factors vital for the desired land use are weighted 1 and non-significant factors are weighted 5. Equation 2.2 derives the final suitability rating for each land parcel.

$$\text{Suitability Score} = \frac{\sum \text{values} > \text{weight } 1}{\sum \text{weight} > 1} * \prod \text{values} = \text{weight } 1 \qquad \text{Equation 2.2}$$

This formula segregates the most influential attributes (having weight 1) from other less important factors (having weight > 1) and multiplies the average suitability values assigned to the less important factors by the product of suitability values. The final suitability score is mainly attributed to the suitability ratings discounted by limiting factors. In this method, the weightings of the factors are assigned arbitrarily whereas the ranking of the factors is used as the basis for deriving the weights in the ordinal scale. The maximum weight value is always equal to the total number of factors being taken into account.

Istituto Agronomico per l'Oltremare (IAO) successfully employed FAO's approach for assessing land suitability for forest plantation and agricultural crops in the Plateau of

Ben Silmane in Morocco. The classes of each land attribute were assigned relative suitability value of 0 for worst condition and 1 for the ideal condition. The final scores derived from Equation 2.2 were transposed into suitability classes, that is, highly suitable (S1), moderately suitable (S2), marginally suitable (S3) and not suitable (N).

2. Analytical Hierarchy Process

In the late 1980s Saaty developed an Analytical Hierarchy Process (AHP) for a comprehensive decision-making, taking into account several factors and their attributes (Saaty, 1977). It analyses a decision problem through a hierarchy of the goal, decision factors, decision sub-factors and their attributes at the bottom level (Figure 2.2).

In the case of land use decision-making, the goal is to determine the land use suitability scores and comprises the first level of the hierarchy. The second level of the hierarchy includes the decision parameters like social, economic or environmental issues for land use under considerations. These parameters are further specified in the next level of hierarchy (third level) as decision factors such as slope, elevation and distance to road. At the bottom of the hierarchy, the attributes of these factors are classified by rating their relative contribution to the goal. The sum of the values of all the attributes for a decision alternative determines its relative suitability.

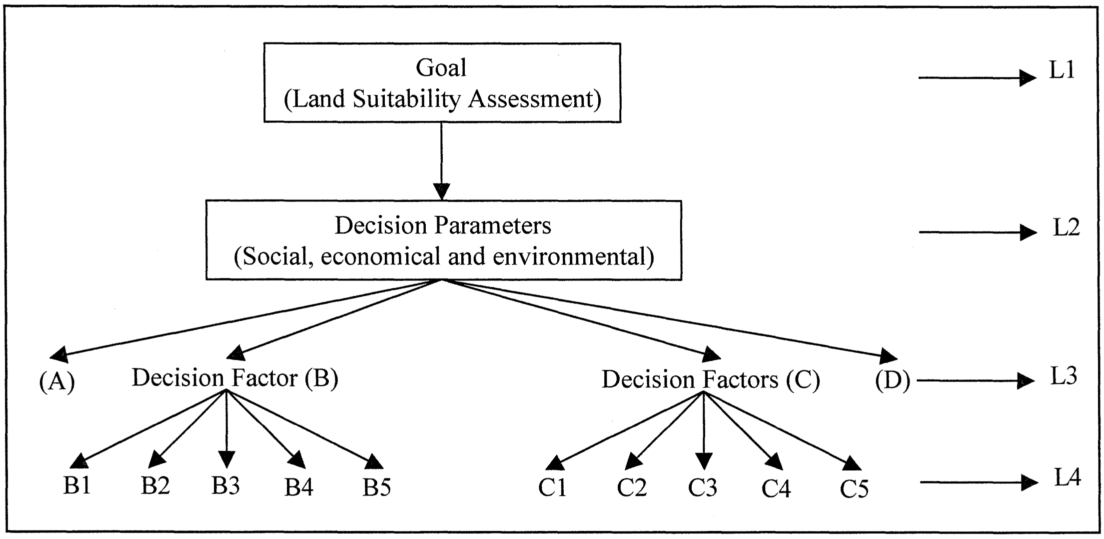


Figure 2.2 Decision hierarchy for AHP process

Recognizing the differences in the relative significance of the factors to the degree of suitability, Saaty developed a pair-wise comparison method to find the relative weight or preference of each factor using a 1-9 scale of comparison (Saaty and Vargas, 1991)

(Table 2.1). The factors are listed in hierarchical order, from most important to least important, and a pair-wise comparison matrix is created assigning a relative significance value for each factor to the rest of the factors between 1 and 9, as given in Table 2.1. An example of a pair-wise comparison matrix is in Table 2.2.

Table 2.1 Scale for pair-wise comparison proposed by Saaty (1977)

SN	Relative weight	Explanation
1	1	Equal importance
2	3	Moderate prevalence of one over another
3	5	Strong or essential prevalence
4	7	Very strong or demonstrated prevalence
5	9	Extremely high prevalence
6	2,4,6,8	Intermediate values
7	Reciprocals	For inverse comparison

Table 2.2 A Pair-wise comparison matrix for deriving relative weights

Factors	A1	A2	A3	A4	Weights
A1	1	2	9	7	0.5426
A2	½	1	6	5	0.3211
A3	1/9	1/6	1	1/3	0.0462
A4	1/7	1/5	3	1	0.0901
Total	1.7539	3.366	19	13.333	1.0000
				Consistency Ratio: 0.04	

Source: Dai *et al.* (2001)

In the example illustrated in Table 2.2, four factors A1, A2, A3 and A4 are compared pair-wise in the matrix by assigning the relative significance value of each factor in the vertical column to all the factors in the corresponding cell. It is necessary to fill only one diagonal half of the matrix; the other half is the reciprocal of the values in the first half. The relative weight of each factor is the value corresponding to the principal *eigenvector* value, which can be estimated by taking the average of weights derived for each cell in the row corresponding to a factor (Saaty, 1980; Eastman *et al.*, 1993). The sum of these values should be one. The higher the *eigenvector* value the higher its relative importance (weight). However, the acceptance of the resultant weight depends on the consistent judgment of relative significance of different factors. The consistency is measured in terms of the probability of random assignment of values in the matrix and is called Consistence Ratio (CR). Its value is derived as the ratio of Consistency Index (CI) and the average of the resulting consistency index (RI). The pair-wise comparison is adequate when the consistency ratio is less than 0.10, otherwise a repetition of the rating is required, to avoid inconsistent ratings (Saaty, 1980).

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \qquad \text{Equation 2.3}$$

$$\mathrm{RI} = \max - \frac{n}{n-1} \qquad \text{Equation 2.4}$$

This procedure has found wide application in multi-criteria decision-making problems in various fields, including land use suitability assessment (Carver, 1991; Eastman *et al.*, 1993; Siddiqui *et al.*, 1996; Eastman *et al.*, 1998; Proctor, 1999; Dia *et al.*, 2001). Eastman *et al.* (1993) incorporated a pair-wise comparison matrix to derive the relative importance of different factors to be used in Multi-Criteria Evaluation (MCE) module in IDRISI® Software. It provides a concrete framework for designing the decision problem; it also allows the use of the user's own criteria and preferences for deriving weights using the pair-wise comparison procedure (Malczewski *et al.*, 1997).

Siddiqui *et al.* (1996) applied the AHP technique in a GIS environment for solving a spatial problem and named it the tool Spatial-AHP. This technique excludes unsuitable areas by using the Boolean maps and assigns relative suitability to the rest of the areas by combining the Relative Importance Weights (RIWs) at each level of hierarchy as per Equation 2.5 (Siddiqui *et al.*, 1996).

$$\textit{Suitability Index} = \sum_{i}^{N2}\left[RIW_i^{\,2} . \sum_{j}^{N3_i}\left(RIW_{ij}^{\,3}\right).RIW_{ijk}^{\,4}\right] \qquad \text{Equation 2.5}$$

This method uses the framework of AHP for formulating a decision problem, as shown in Figure 2.2 and derives the RIWs at each level by pair-wise comparison. This method does not use absolute values of the factors/attributes, whether in an ordinal or interval scale to define land use requirements. These values are estimated in a ratio scale between 0 and 1 by a pair-wise comparison signifying their relative contribution to the primary goal. However, this method has not yet been compared with other methods. It treats each factor separately at each level and combines their values based on their relative weights, therefore, it tends to avoid the compensatory effect of one good factor over another poor factor.

3. Weighted Linear Combination (WLC)

Voogd (1983) incorporated the relative weight of factors to combine multiple criteria for assessing suitability. This rule of combination is called Weighted Linear

Combination (WLC). Here, each criterion contributes quantitatively to the evaluation and may compensate for other criteria. It means that a criterion with poor class may be compensated by several criteria with good classes, thereby giving overall an above average class (Nijkamp *et al.*, 1990; Eastman *et al.*, 1993). The sum of all the weights always equals one and is usually derived by the pair-wise comparison method. This technique has been widely used as a rule of combination for decision-making based on Multi-Criteria Evaluation (MCE). The factor maps are simply added together after the attribute values have been multiplied by their relative weights. The value of each cell in the suitability model is given by Equation 2.6.

$$Suitability = \sum w_i x_i \qquad \text{Equation 2.6}$$

Where w_i is weight for factor i and x_i the cell value for factor i.

This procedure has also been included in the Multi-Criteria Evaluation (MCE) module of IDRISI®. The MCE module combines several factor maps after multiplying the attribute values by their relative weights and generates a suitability map for a land use based on the criteria and the relative weights. When constraints are involved, the suitability (S) is derived by multiplying the sum of the weighted value ($\Sigma w_i x_i$) by the product of constraints (ΠC_j) as shown by Equation 2.7. The constraint maps are created by using Boolean logic, 0 to the constraint area and 1 to the non-constraint area. Inclusion of constraints in the equation excludes the areas under constraint from the suitability map without altering the suitability values of the land unit.

$$Suitability = \sum w_i x_i * \prod C_j \qquad \text{Equation 2.7}$$

Dai *et al.* (2001) employed the Weighted Linear Combination method for land use suitability assessment for four categories of urban land use. The relative weights for the factors were estimated by using the pair-wise comparison and the final suitability map for each land use alternative was derived by combining all the factor maps using the WLC method. In another example, Ceballos-Silva and López-Blanco (2003) assessed the suitability of agricultural crops (maize and potato) in Central Mexico by using the WEIGHT and MCE module in IDRISI®. The WEIGHT module uses pair-wise comparison for estimating the relative weights of the various factors. The Weighted Linear Combination (WLC) option available in the MCE module was used to derive the final suitability map for each crop.

Bojórquez-Tapia *et al.* (2001) also used the WLC method for assessing land suitability. However, they derived the relative weight of factors in an ordinal scale by using the following Equation 2.8.

$$W_{ij} = n_j - r_{ij} - 1 \qquad \text{Equation 2.8}$$

Where W_{ij} is the weight for factor i land use j, n_j is the total number of factors for land use j and r_{ij} is the rank of the factor in an ordinal scale for land use j.

Nehme and Simões (1999) pointed out that the subjective nature of weighting is a problem in the WLC method. In land use decision-making, the objective weighting may not be as appropriate as the subjective weighting. The subjective weighting of factors enables the decision makers to reconcile the conflicts of interest and preferences among the diverse group of stakeholders with different social, economic and environmental backgrounds.

The classification of the factor's attributes in the ordinal and continuous scale is widely used before applying the Weighted Linear Combination to combine the multiple evaluation criteria. The use of fuzzy logic in representing the factor attributes has been recently developed and described as more appropriate for classifying attributes for land use suitability assessment (Hall *et al.*, 1992). The next sub-section reviews the application of fuzzy logic in land suitability assessment.

I. Fuzzy logic in land use suitability assessment

In contrast to the Boolean logic, fuzzy logic accounts for the 'continuity and uncertainty' in the attributes (Jiang and Eastman, 2000), imitating the natural basis of understanding of the human brain (Zadeh, 1987). Fuzzy set theory has become an important mathematical tool in dealing with the world of inexactness and error in measurement (Burrough, 1989). Land suitability assessment requiring classification of continuous data such as slope, soil, elevation has found fuzzy logic very useful (Burrough, 1989; Burrough *et al.*, 1992; Hall *et al.*, 1992; Jiang and Eastman, 2000).

Fuzzy logic classifies an attribute in a continuous scale by assigning values between 0 and 1 as determined by their closeness to the defined class. An attribute class exactly matching the defined class is assigned a membership value of 1, whereas if a class fails to satisfy the defined class, it is assigned 0 (see Burrough *et al.* 1992). Mathematically, a fuzzy set ***A*** for an attribute class x in the population ***X*** is given by Equation 2.9.

$$A = \{x, \mu_A(x)\} \qquad x \in X \qquad \text{Equation 2.9}$$

Where $\mu_A(x)$ is the membership function value in the range 0 to 1.

The membership function of attribute x in A may be derived by using a Similarity Relation Model (SR) or a Semantic Import Model (SI) (Burrough, 1989). However, Burrough suggested the SI method would be simple and appropriate when a good knowledge of classifying data exists. The primary membership function is given by a symmetirical bell-shaped membership function as shown in Figure 2.3; this can be stated by Equation 2.10 for defining membership value for different land attributes (Burrough *et al.*, 1992; Kollias and Kalivas, 1998).

$$MF_x = \left[\frac{1}{1+\{(x-b)/d\}^2}\right] \qquad \text{for } 0 \le x \le P \qquad \text{Equation 2.10}$$

Where b is the central value and d is the width of transition zone.

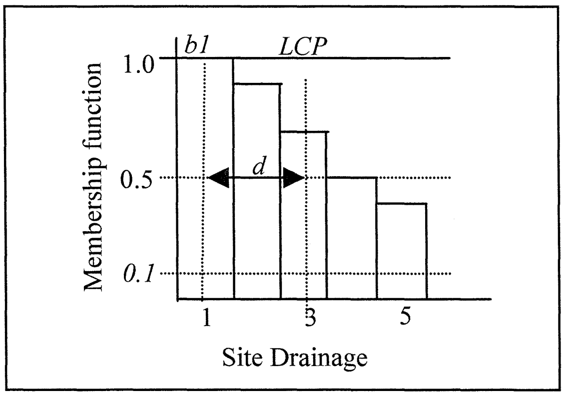


Figure 2.3 Membership function for single ideal point

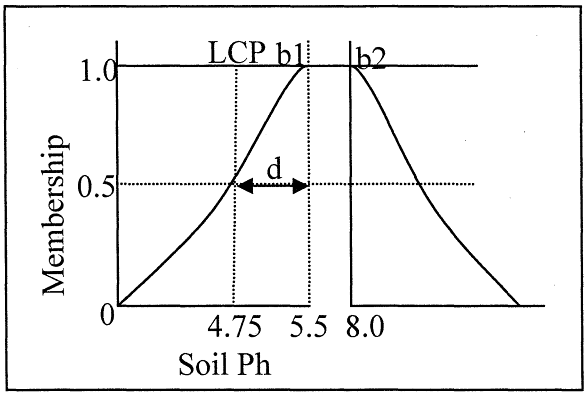


Figure 2.4 Membership function for multiple ideal points

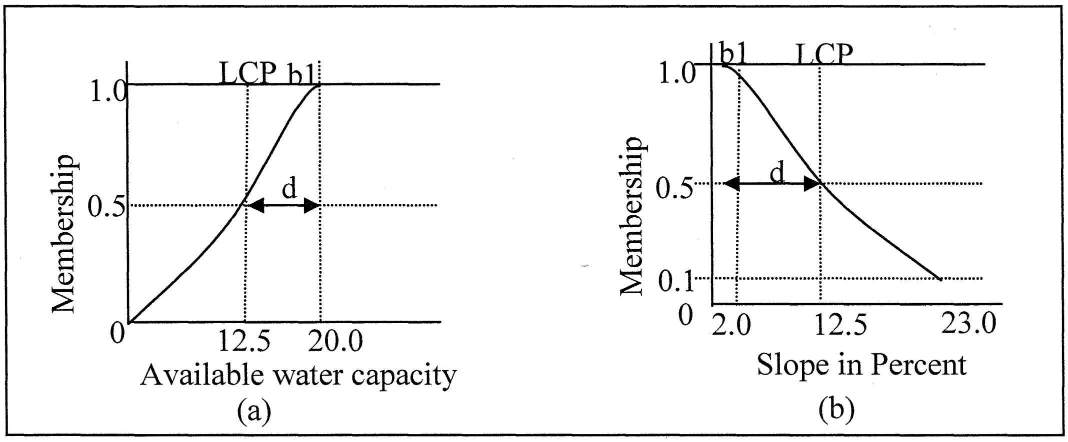


Figure 2.5 Membership function for assymetric left (a) and right (b) models

These membership functions can be modified to provide fuzzy membership classification for parameters with multiple ideal points and which are asymmetric on either the left or right side (Figures 2.4 and 2.5). These models require definition of a lower threshold value, a central value and an upper threshold value for each attribute. Subsequently, the appropriate model is determined by the class relationship to the attribute as found by the attribute classification approach. After finding a fuzzy membership value for each attribute, the Joint Membership Function (JMF) is obtained by using a convex combination of all the fuzzy subsets i.e. $A_1 \ldots\ldots A_n$ and their respective weights (w_j) as given by Equation 2.11 (Burrough, 1989).

$$\mathrm{JMF} = \sum_{j=1}^{k} w_j \mu_{Aj} \qquad \text{Equation 2.11}$$

There have been several papers published on the application of fuzzy set theory to real land evaluation problems. Burrough (1989) first applied this logic to land suitability assessment for different crop production in Venezuela and Kenya. This approach was compared with the Boolean method for assessing land suitability for expansion of a research site in Alberta, Canada by Burrough *et al.* (1992) and also for land suitability for agriculture in Java, Indonesia by Hall and Wang (1992). Both studies revealed that the fuzzy method was more flexible as well as more realistic than the Boolean method for land suitability assessment. In order to enhance the GIS capability for spatial analysis and decision-making, the fuzzy classification approach has also been incorporated into the ARCInfo GIS software for land evaluation purposes (Kollias and Kalivas, 1998).

Basnet *et al.* (2002) also used fuzzy methods for assessing land suitability for manure application using GIS. The bio-physical, social and environmental factors were classified in a fuzzy scale assigning a value between 0 and 1 to a class defining the degree of suitability. Linear scaling equations were used for fuzzy classification of the factor attributes. Equation 2.12 was used when the largest value has the best suitability and for the opposite case, Equation 2.13 was used.

$$X_{ij} = \left(\frac{R_{ij} - R_{\min}}{R_{\max} - R_{\min}} \right) \qquad \text{Equation 2.12}$$

$$X_{ij} = 1 - \left(\frac{R_{ij} - R_{\min}}{R_{\max} - R_{\min}} \right) \qquad \text{Equation 2.13}$$

where X_{ij} is the value of *ij* cell in fuzzy scale, R_{ij} is the value of *ij* cell, $R_{\max}$ is the maximum cell value and $R_{\min}$ is the minimum cell value.

Owing to their varying significance for the degree of suitability, factor classes were changed into weight values between 0 and 1 by pair-wise comparison using WEIGHT module in the IDRISI software® (Basnet *et al.*, 2001). The factors were also weighted to assign values signifying their relative influence on the degree of suitability. The relative importance of each factor was estimated based on their ability to achieve the underlying objectives of land suitability assessment. The method has been called the Objectives-Oriented Comparison (OOC) and is undertaken by a direct consultation (for example interview) with the stakeholders. The group will decide on the relevance of the factor to each objective by assigning 1, 0.5 and 0 to relevant, partially relevant and not relevant, respectively. The total values derived from the OOC provide a consistent judgment of the relationship between the factors for the pair-wise comparison in the AHP procedure.

The factor models are combined together to arrive at a suitability value for each cell by using the Weighted Linear Combination (WLC) (Equation 2.14).

$$S_i = \sum_{j=1}^{n} (f_{ij.\mathrm{suit}} * w_j) \qquad \text{Equation 2.14}$$

Where S_i is the overall suitability value for cell i, $f_{ij.\mathrm{suit}}$ is the cell value for factor j and w_j is the weight for the factor j.

2.3.3 Decision support tool

Multiple criteria, conflicting land uses and socially and economically heterogeneous stakeholders add complexity to any land use decision-making. Even if a consensus is arrived at on the criteria and rules for combinations among stakeholders and decision makers, making a decision on land use allocation for single or multiple land uses is still a challenging and difficult task where there are several potential land parcels available for the desired land use alternative(s). Manual methods become inadequate to handle the huge amounts of geographical and attribute data involved (Tomlin and Johnston, 1988).

Different decision support tools have been devised to deal with multiple criteria and also conflicting land use types in order to generate a scientifically rational land use allocation alternative (Hall *et al.*, 1992). However, the tool only offers decision alternatives to the problems based on the chosen criteria and decision rules. The stakeholders and the decision maker can make modifications to the number of criteria, their coding and also the rules for combining them to arrive at an alternative land use allocation. They may be satisfied with the land use allocation delivered or may change it before making a final decision. The available decision support tools in regard to land use decision-making will be described in the following section.

2.3.3.1 Multi-criteria decision-making (MCDM)

MCDM has been classified into two broad groups: Multiple Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM) (Hwang and Yoon, 1981; Malczewski *et al.*, 1997). The former group involves the choice of the best alternative from a small number of discrete options, whereas the latter is a design problem that has an infinite number of possible solutions in a continuous solution space. The MADM evaluates a limited number of alternatives based on multiple criteria; it has also been called Multi-Criteria Evaluation (MCE) or Multi-Criteria Analysis (MCA) (Janssen and Rietveld, 1990; Carver, 1991). If there is an infinite number of possible solutions or all the solutions are unknown, the problem becomes a design problem and therefore lies within the scope of the MODM. The MODM category of MCDM is also known as the optimisation technique and uses mathematical programming and heuristic methods to provide an optimum solution to a problem (Aerts, 2002). Figure 2.6 summaries the various techniques of the MCDM, and the following paragraphs elaborate these approaches.

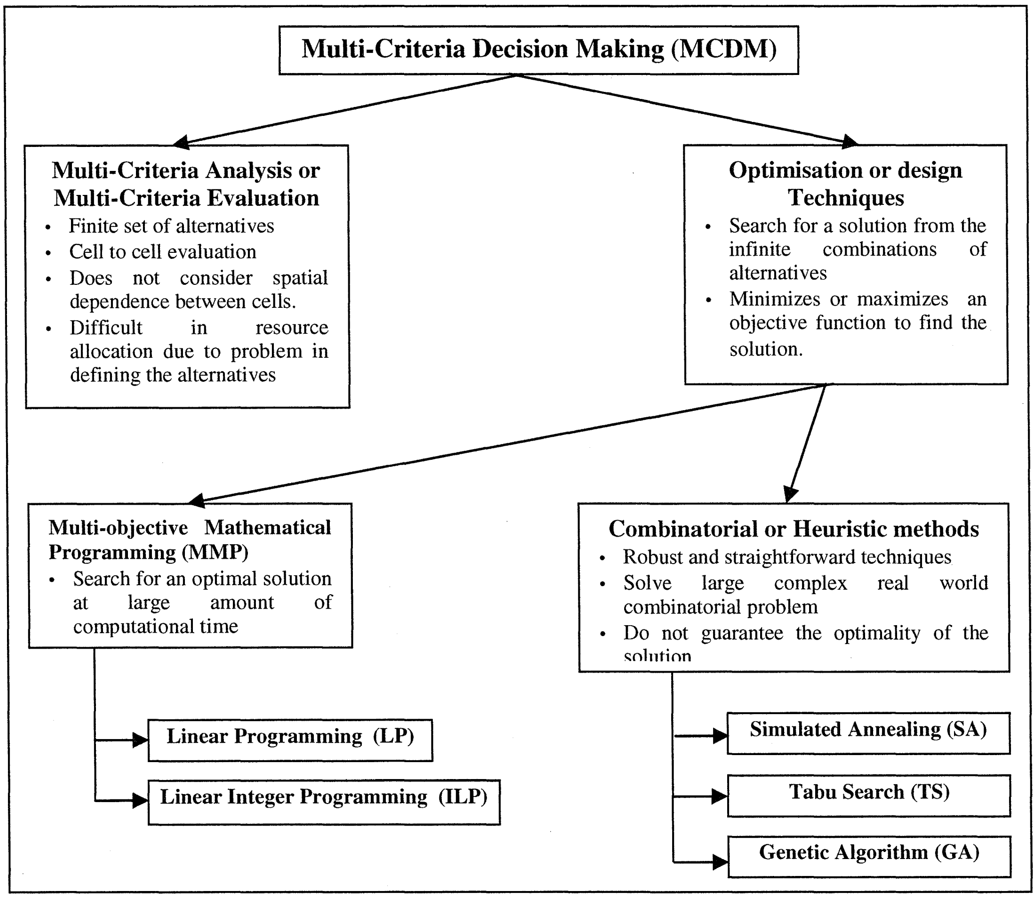


Figure 2.6 Multi criteria decision making approaches in land use decision-making

1. Multi Criteria Evaluation (MCE)

Multi-Criteria Evaluation or Analysis has been developed to facilitate decision-making in regional planning and takes into account multiple, conflicting and non-commensurate decision variables (Carver, 1991). MCE was described as an approach to investigate a number of choice possibilities in the light of multiple criteria. It can handle a small number of options and a limited number of criteria, with a maximum of eight alternatives and the same number of criteria (Voogd, 1983). The best possible alternative is chosen by evaluating the known alternatives based on specified criteria and is, therefore, also known as an 'evaluation technique' (Aerts, 2002: 18).

MCE can be classified into compensatory and non-compensatory techniques based on the approaches used for evaluating the available alternatives. In the compensatory approach, all the criteria are taken into account in order to find an overall evaluation parameter for each alternative solution. The aggregated parameter reflects a combined value of all the criteria, where the high value of one criterion counteracts the low value of another criterion. The relative weights of criteria may be used to combine them in order to incorporate their relative importance to the alternative. This is also called a 'complete aggregation technique' (Joerin *et al.*, 2001). Weighted Linear Combination, Ideal Point Analysis and Concordance-Discordance analysis are compensatory MCE techniques. The non-compensatory approach uses a direct comparison of criteria and avoids trade-offs between criteria. The search is limited to the selected criteria and is also called a 'partial aggregation method' (Joerin *et al.*, 2001). This approach involves the Dominance model, Conjunctive and Disjunctive models, Lexicographic Ordering, Hierarchical Optimization and Outranking method (Hong and Vogel, 1991). Joerin and Musy (2000) demonstrated the application of the non-compensatory MCE technique to land use decision-making using the partial aggregation of the criteria and avoiding comparison of incomparable alternatives.

Carver (1991) demonstrated the applicability of MCE techniques to complex land use decision-making involving several land use alternatives with different attributes. Carver applied three MCE techniques, after some modifications, and integrated them with GIS to evaluate potential sites for disposing of nuclear waste. These techniques were Ideal Point Analysis (IPA), Hierarchical Optimisation (HO) and Concordance-Discordance Analysis (CDA). In IPA, an ideal solution is assumed based on the criteria used and the quality or appropriateness of each solution (alternative) is assessed with reference to the ideal solution. In CDA, the pair-wise comparison of the available alternatives is the main basis of evaluating the alternative solutions. The HO involves ranking of criteria based on their relative importance and follows the evaluation of alternatives based on their ability to satisfy the prioritised criteria.

Eastman *et al.* (1993) used a weighted linear combination (WLC) as a compensatory MCE technique to find relative suitability by combining several continuous factors, after normalization and relative weighting. The relative weights were derived by pair-wise comparison of the criteria. Other MCE techniques involve Order Weight Combination (OWC) and Boolean intersection. All three MCE techniques have been integrated into MCE module in IDRISI® GIS software.

2. Multi Objective Decision Making (MODM)

Multi objective decision making techniques are specifically designed to handle problems which have an indefinite number of possible alternative solutions. Many real-world problems are of this type and fall within the scope of the MODM. These techniques tend to find an optimum solution through designing the best possible combination of alternatives in which all the conditions set forth by the decision makers are met (Hwang *et al.*, 1979). These are also called ‘optimisation’ or ‘design techniques’ (Aerts and Heuvelink, 2002). The aim of optimisation is to find a best compromise solution through combining all the decision variables and meeting the specified constraints.

The optimisation goal is expressed in mathematical form as the objective function to be maximized or minimized (CSEP, 1996). There are several optimisation techniques that can deal with different types of optimisation problems. Hwang *et al.* (1979) reviewed the MODM techniques and categorized them into three broad groups, based on inclusion and/or exclusion of decision makers preferences. However, in the case of land use decision-making, the MODM techniques can be classified into two groups: the mathematical programming technique and heuristic algorithms. These techniques are described briefly here.

I. Mathematical Programming Techniques

The mathematical programming techniques were employed to facilitate the land use decision-making process through generating non-inferior sets so that a best solution could be chosen (Brill *et al.*, 1982). Though the linear programming technique provides an optimal solution to problems having an objective function and where all the constraints are linear (Foulds, 1984), it may not be an appropriate technique for solving problems that are non-linear in character, like land use allocation problems.

However, the objective of allocating only one land use to one land parcel makes such a problem an integer type, which is therefore solvable by integer programming methods (Aerts, 2002). Gilbert *et al.* (1985) demonstrated the application of multi-objective integer programming to allocating residential land use in the Norris area in Tennessee, USA. They attempted to optimise four objective functions: cost, distance to desirable and undesirable land features and the shape of the area. These were defined as sub-problems solved by using an integer-programming technique, included in a program called MOLANDA (Multi-objective Land Allocation). Malczewski *et al.* (1997) developed a Multi-criteria Group Decision Making model by integrating AHP and integer programming methods. The model was tested by allocating nine land use types to 32 land units in the Cape Region, Mexico. Aerts (2002) also demonstrated the application of integer programming to three land use allocation problems. These models have demonstrated the usefulness of mathematical programming techniques for delivering a non-inferior solution to single or multiple land use allocation problems.

The size of the problem was found to be crucial to the usefulness of the mathematical programming method. The size of the problem determines the computational time and this tends to grow by polynomial time. Though the mathematical programming techniques deliver an optimal solution, the computational time increases with the size of the problem and thus it may not be solved within an acceptable period of time. The entire evaluation of all possible solutions becomes computationally not feasible in the case of larger-size problems. Aerts (2002) concluded that the integer programming method could not solve problems with a matrix of larger than 50 by 50 cells. Such problems have been classified as 'Non-deterministic Polynomial-time hard or complete' (NP-hard or NP-completeness) problems and they attracts another group of MODM techniques called combinatory methods or heuristic algorithms (Aarts and Korst, 1989). The combinatory methods will be discussed briefly in the next section.

II. Combinatory methods or heuristic algorithms

The heuristic algorithms are capable of solving combinatorial problems generating a solution close to an optimal solution through minimization or maximization of an objective function; these optimisation techniques may also be called combinatorial methods. Combinatory methods or heuristic algorithms have been specifically developed to handle NP-hard or NP-complete problems by delivering a sub-optimal solution in an acceptable time. Those NP-hard or NP-complete problems having discrete control variables are a group of problems that require an optimum permutation of all the control variables. The search for each permutation of the control variables for a NP-hard problem is exhaustive and computationally not feasible as the time grows by polynomial time. Such problems have been categorized as 'combinatorial optimisation problems' (Otten and van Ginneken, 1989; CSEP, 1996).

The heuristic algorithms trade off the optimality of the solution to the computational time. The solutions are not exactly optimum solutions; rather, they are sub-optimum or near to optimum solutions, obtained within reasonable amounts of time. As the solutions delivered by these algorithms are approximate solutions, the algorithms are also called 'approximation algorithms' (van Laarhoven and Aarts, 1987). Based on the scope of the approximation algorithms, an algorithm can be categorized either as a 'tailored algorithm' or a 'general algorithm'. The Simulated Annealing, Genetic Algorithms and Tabu Search are viewed as general approximation algorithms applicable to a wide variety of combinatorial optimisation problems (Pirlot, 1996). A list of combinatorial methods and examples of the real world problems which have been successfully solved by these combinatorial methods is given in Table 2.3. This research aims to apply the Simulated Annealing and Tabu Search in solving the MOLAA problem and to compare their performances.

Table 2.3 Combinatory methods used for solving real world combinatorial optimization problems

S. N.	Name of the algorithm and abbreviation	Application	Authors
1.	General Purpose Simulated Annealing (GPSIMAN)	General application	(Connolly, 1992)
2.	Genetic Algorithm	Land use allocation	(Stewart *et al.*, 2004)
3.	Simulated Annealing	Graph Colouring and number partitioning	(Johnson *et al.*, 1991)
4.	Simulated Annealing	Police District Design	(D'Amico *et al.*, 2002)
5.	Simulated Annealing	Trusses Design	(Hasancebi and Erbatur, 2002)
6.	Simulated Annealing	Harvesting Scheduling	(Lockwood, 1993)
7.	Simulated Annealing	Spatial Optimisation	(Trap and Helles, 1997)
8.	Simulated Annealing	Multi-objective land use allocation	(Aerts, 2002; Aerts and Heuvelink, 2002)
9.	Tabu Search	Harvesting Scheduling	(Bettinger *et al.*, 1997; Boston and Bettinger, 1999)
10.	Tabu Search	Job-shop scheduling	(Dell'Amico and Trubian, 1993; Brandimarte, 1993)
11.	Tabu Search	Quadratic assignment problem	(Taillard, 1991)
12.	Simulated Annealing	Circuit Design	(Kirkpatrick *et al.*, 1983)
13.	Genetic Algorithm Land Allocation Decision Support System (LADSS)	Multi-objective land use planning	(Matthews, 2001)

2.3.3.2 GIS application in land use decision-making

Geographic information system (GIS) was developed to combine different fields of spatial data handling into a single system (Burrough *et al.*, 1992). The system encompasses all aspects of spatial representation from data capture to display of an output, as well as intermediate operations like storing, retrieval, manipulation, analysis and query of the spatial data. Land is the primary geographic or spatial object of interest, thus GIS has been used widely used in land use planning and decision-making (Tomlin and Johnston, 1988; Heit, 1991; Martin, 1996). One of the analytical capabilities of present day GIS is due to the 'overlay technique', which came out of McHarg's manual on the overlying of thematic maps for land use planning (Lees, 2004). The following sections briefly describe the history of the use of GIS in land use decision making, from McHarg's pre-GIS approach to the present application of GIS to land use decision-making.

1. Pre-GIS approach: McHarg's method

Thematic maps representing a particular feature of the earth have been found to be useful in decision-making from early times. In the early stages, the production of thematic maps was a very costly and tedious process because of inadequate techniques for handling the earth's continuous features, the difficulty in classification and problems encountered in discrete representation of the earth's features. Therefore, the use of thematic maps was determined by the ease of their production (Lees, 2004). Before the advances in the techniques for thematic mapping, McHarg (1969) produced thematic maps manually for various natural features categorized into consistent regions using graduated shades of grey colour. These thematic layers were put together or overlaid on a light table and suitability values for different land uses were interpreted based on the lightness or darkness of the shade. McHarg used this approach to provide an ecological plan for the Potomac River Basin in the USA. He regarded the basin as an 'interacting process' and took into account various natural phenomena like climate, geology, hydrology, soils, physiography, vegetation, wildlife and man-made features such as accessibility, to determine the areas that were suitable for agriculture, forestry, recreation and urban development. The multiple uses of the land were assessed by the compatibility of these land uses and finally a composite suitability map for the basin was derived. This approach later became known as 'McHarg's light table method' (Steiner, 1983). Though the approach is considered very primitive in today's context and with advances in GIS technologies, it provided the foundation for the 'overlay method' of present GIS analysis capability (Lees, 2004).

In a Metropolitan planning exercise, McHarg (1969) used a different approach to combine attributes for identifying suitable areas for urbanization. First, land units with the attributes that did not favour urban use were identified. These areas were subsequently excluded from urban use. Secondly, the potential land areas were assessed and ranked for their strength for construction and suitability for septic tanks based on soil properties. The ranking of land units based on their suitability enabled identification of the most suitable land for urban use. The process revealed a sequence of sieving operations and is therefore called 'McHarg's Sieving method'. Both McHarg's methods were very subjective and the datasets involved were nominal data types.

2. GIS based approach

Even though there had been considerable developments in GIS technology, these were not applied to their full potential to deal with real world problems. Until the late 1980s, GIS technology was not appreciated as a tool in land use decision-making. The digital mapping technique and map algebra have made it possible to use GIS in land use decision-making. Tomlin and Johnston (1988) realized the potential of GIS technology in land use data capturing, storing, manipulation and analysis, and attempted to verify it by investigating a hypothetical land use allocation problem in Illinois, USA. They considered sixteen land use types relevant for the areas. These land use types were allocated based on their land characteristic requirements (site criteria) and also the predetermined relationships between two land use types (situation criteria). Selected criteria were used to assess the suitability of each land use type by assigning relative values. Criteria maps using digital databases were overlaid to reveal the overall suitability of each land use type. The minimum area for each land use type was used to identify feasible and non-feasible areas. Iterative processes accomplished the final allocation to each land use type, achieving a predetermined spatial relationship between any two land use types. Tomlin and Johnston (1988) found the technique delivered a satisfying and appropriate outcome for making land use decisions.

Openshaw *et al.* (1989) also used GIS techniques to aid decision-making in locating a suitable site for dumping nuclear waste. The problem was a single objective location problem but was evaluated using multiple criteria namely population, geology, access and conservation. Overlay and buffer operations were carried out to combine these attributes and finally, potentially feasible sites for low and intermediate level radioactive wastes were located, based on the Boolean search method. These operations and search methods proved useful in identifying an area which simultaneously met all these criteria. The successive overlay of criteria maps specifies the area which meets all the specified criteria. But it does not provide any clues to the decision maker about which sites within the defined feasible area offer the best combination of site-specific characteristics. However, these operations are straightforward and simple, and do not involve any analytical capability to evaluate the suitability of the area within the feasible area to aid the decision making (Carver, 1991). Carver also found that the existing GIS techniques were of limited use when multiple objectives and several conflicting criteria were involved.

3. Integrating other methods with GIS

These initial efforts of applying GIS as a decision support tool in land use issues provided a crucial step for further development. The limitations of the existing techniques prevented GIS from being very useful as a decision support tool in complex land use problems involving non-deterministic, multiple and conflicting attributes. However, the ability of GIS in data acquisition, storing, manipulation and visualization provided an essential framework for its integration with other analytical or optimisation tools outside GIS (Grabaum and Meyer, 1998). Many efforts have been made to integrate other methods capable of performing spatial analysis into the GIS. Integration of other methods with GIS has greatly enhanced the spatial analytical capability of GIS and has made it a powerful planning tool that can facilitate decision-making by enabling generation of different, alternative solutions for different scenarios. The following sections describe some of the decision support tools developed for single/ multiple land use allocation decision-making through integrating other methods with GIS.

I. For single land use allocation problems

Carver (1991) first attempted to combine three Multi-Criteria Evaluation (MCE) techniques within a GIS framework to locate suitable sites for storing radioactive waste material in the UK. The incorporation of the Multi-Criteria Evaluation techniques enabled combination of a wide range of criteria using different weights for unbiased and explicit comparisons among all potential sites. Carver used three MCE methods for evaluating potential sites revealed through applying primary siting criteria. An Multi-Criteria Evaluation technique programmed outside GIS was linked through a macro language to evaluate potential sites using a GIS database created for specific site characteristics. Carver found that a best compromise solution for nuclear waste disposal could be displayed using GIS. This integration of MCE with GIS thus has potential for developing a Spatial Decision Support System for single facility location problems.

'MAGISTER', an acronym for Multi-criteria Analysis with GIS for TERritory, decision support model combining the MCE and GIS (Joerin and Musy, 2000). The input data handling, management and spatial analysis are carried out by using a GIS package, whereas the data compilation and evaluation of all the alternatives to arrive at the best selection of the alternative is accomplished by the MCE technique. The model relies on an outranking method called ELECTRE developed by Roy (1981) for comparing alternatives. Though this method can handle only a limited number of alternatives, it avoids the comparison of entirely different alternatives. In order to reduce the number of alternatives, the alternatives are compressed based on a homogenous index by using threshold values for non-difference, strict difference and veto as determined by the decision makers. This model was implemented for allocating land for residential purposes in the area of Vaud, Switzerland. The model is interesting for single land use allocation problems and involves many people in the decision making process. However, the authors did not mention using this model for multiple and conflicting land use allocation problems.

II. For multiple land use allocation problems

Eastman *et al.* (1993) appreciated the growing scope for making GIS in policy decisions through providing informed choices to the decision makers and in resource allocation decisions through explicit evaluation of different alternative resources. Eastman and his team worked extensively on land use decision-making problems and arrived at GIS solutions for different typologies of land use decision-making through integrating different MCE techniques with GIS. Three MCE techniques, Weighted Linear Combination, Order Weight Combination and Boolean intersection have been incorporated into the IDRISI® GIS software (Eastman, 2001). These techniques combine factor maps based on their relative weights and exclude the areas specified by Boolean constraint maps. The output serves as a suitability map revealing the relative suitability of each cell. The relative weight of a factor can be derived from different weight schemes. The pair-wise comparison, one of the most widely accepted methods for determining relative weight (Proctor, 1999), has also been incorporated in the software. This MCE module has proven useful for providing decision support in single objective problems with single or multiple criteria (Eastman *et al.*, 1998). The GRASS (Geographic Resources Analysis Support System) software has also built in the capacity for doing MCE based on the WLC method (Bojórquez-Tapia *et al.*, 1994). These MCE modules are able to create a suitability map based on multiple criteria but are not adequate for providing the decision support for multiple and conflicting land use decision-making.

Except for the single facility location problem, land use planning should take into account the multi-functionality of the landscape and therefore involve optimum allocation of multiple land uses. Realizing the demand for a decision support tool to allocate multiple and conflicting land uses, Eastman *et al.* (1993) developed a Multi

Objective Land use Allocation (MOLA) module by applying the Multi Criteria Evalution (MCE) in a GIS environment. This is one of the methods chosen for this research to compare the results with other methods by solving the same MOLAA problem. A detailed description of the MOLA procedure is given in Chapter 3. Bojórquez-Tapia *et al.* (2001) used multi-criteria evaluation (MCE) to evaluate each land use option based on the defined criteria and later completed a multi-objective analysis by using multivariate numerical classification through a divisive polythetic partitioning, to combine land units into four land use types. The relative suitability of each pixel was assessed from the relevant criteria for each land use type using the Multi-Criteria Evaluation technique in Unix-based GIS software called GRASS. The weighted linear combination of the criteria and subsequent normalization of suitability values to a 1 to 10 scale were carried out to make a comparison of the relative suitability of land use types. The multi-objective analysis was carried out using the Principle Component Analysis (PCA) technique to segregate the total area into groups of homogenous land units. The relative suitability of different land use types in comparison with these homogenous units was instrumental in deciding between exclusive dominance or competition between two or more land use types. The land use conflict was resolved either by allocating the area to the highest suitability land use or by a negotiated solution guided by environmental principles. This numerical classification procedure is claimed to be easily understandable by all stakeholders and quicker than the alternative methodologies such as Analytical Hierarchy Process or fuzzy logic (Bojórquez-Tapia *et al.*, 2001).

Malczewski *et al.* (1997) devised a Multi-Criteria Group Decision Making model (MCGDM) for land use decision-making based on the AHP and mathematical integer programming. The AHP method was used to reconcile the conflicting interests and preferences of different stakeholders by pair-wise comparisons. The model was tested for its suitability for making a consensus decision on allocation of nine land use types in 32 land parcels based on their suitability in Cape Region, Mexico.

2.4 Summary

This chapter has discussed the framework for land use decision-making which will be applied to solving a MOLAA problem. For a MOLAA problem at a regional scale, the decision maker should first identify all stakeholders having an interest in land use planning in the region. The stakeholders will be the focal point in the land use decision-making process. They will express their land use objectives and preferences which will be the basis for identifying land use types and the area required for each land use type. The stakeholders may also present many criteria for assessing the relative suitability of each land use type. However, the selection of criteria will depend on the available information/data and resources available. Combining the selected evaluation criteria is a crucial step in land use decision-making framework. The decision rule plays a greater role in land use suitability assessment.

This chapter briefly reviewed qualitative and quantitative land use suitability assessment approaches in the context of multi-objective land use decision-making. Land use suitability assessment indicates the relative suitability of each land use type using multiple criteria and a decision rule. However, allocation of single or multiple land uses to the potential land units requires a decision support tool for handling the massive amount of bio-physical data needed for generating decision alternatives. Several approaches and techniques have been developed to solve such land use allocation problems. This chapter has briefly described some of the different approaches to multi-criteria decision-making (MCDM) and the application of GIS to land use decision-making. Chapter 3 will elaborate on three methods (Simulated Annealing, Tabu Search and MOLA, the GIS based technique which will be compared for solving the same MOLAA problem in this research.

Chapter 3

METHODS FOR MULTI-OBJECTIVE LAND USE ALLOCATION

3.1 Introduction

After assessing the suitability of each land use, the next major task in land use decision-making is to allocate multiple land uses by satisfying conditions such as area requirement, shape, and adjacency. Different methods of Multi Criteria Decision-Making can be employed in solving multi objective land use allocation problems (discussed in Chapter 2). Among these methods, this research focuses on the MOLA module in IDRISI® GIS software and the combinatory methods. Simulated Annealing and Tabu Search have been chosen among the combinatory methods in order to compare their performance with that of the MOLA module in solving the same land use allocation problem. The next section briefly describes the theoretical background of the combinatorial optimisation methods and provides a detailed explanation of each of these methods.

3.2 Combinatorial methods

A MOLAA problem resembles the formulation of a general combinatorial optimisation problem. Mathematically, the optimisation goal of these methods can be expressed in the form of an objective function that is to be minimized or maximized (CSEP, 1996). In a minimization problem, the objective function becomes the cost function (F) and S represents the possible configuration of land use options and land parcels in the MOLAA problem (Equation 3.1)

$$F : S \rightarrow R \qquad \text{Equation 3.1}$$

where R assigns a real number to each configuration.

Though the optimum solution (i_{opt}) lies within the solution space S, the combinatorial methods cannot find the optimum solution (Foulds, 1984). Therefore, an acceptable solution, $F_{(i)}$ close to the optimum solution is found when the following condition is met (Equation 3.2):

$$F(i_{opt}) <= F_{(i)} \qquad \text{for all } i \in S \qquad \text{Equation 3.2}$$

Combinatory methods or heuristic algorithms provide a solution that is better than that achieved by the local search by generating a sub-optimal solution close to the global minimum through avoiding entrapment at a local minimum (Pirlot, 1996). The local search methods only accept a solution with lower cost function than the previous solution and finally reach a solution where the cost function cannot be further improved over a specified number of iterations. However, these methods use a different strategy to the local search method and occasionally accept solutions even with a higher cost function. Such moves obviously increase the cost function values but help to avoid being trapped in a local minimum. They finally deliver a better solution closer to the global minimum than that reached by using the local search methods. Combinatorial methods like Simulated Annealing and Tabu Search may provide better solutions by improving the cost function through escaping the local minimum. These methods may not reach the global optimum but will most likely reach a sub-optimal or near-global minimum. A detailed description of the Simulated Annealing and Tabu Search algorithms and their application to a MOLAA problem is provided in the following sections of this chapter.

3.2.1 Simulated Annealing

The Simulated Annealing algorithm is a general approximation algorithm which has found wide application in combinatorial optimisation problems in many fields (CUP, 1992; Pirlot, 1996). This algorithm was derived from 'thermodynamics and metallurgy' (Ulungu *et al.*, 1999: 222) or 'statistical physics' (van Groenigen and Stein, 1998: 1078). The simulation begins by heating the system into a molten state and subsequently slowly cooling the system down by allowing enough transitions to reach the thermal equilibrium at each temperature step; this is called 'annealing'. The annealing process leads to a very stable low energy crystalline structure, whereas the rapid cooling, called 'quenching', produces a metastable non-crystalline structure (Kirkpatrick *et al.*, 1983). The final structure of the solid is the outcome of the cooling process, depending upon whether or not the thermal equilibrium is attained at each temperature. Kirkpatrick *et al.* (1983) and Černeý (1985) independently observed the similarities between the physical process of annealing and the optimisation of combinatorial problems. They eventually demonstrated the application of the algorithm for solving combinatorial optimisation problems (Aarts and Korst, 1989; Nelson and Liu, 1994). As this algorithm has its origin in a simulation of the annealing process, it is commonly known as a 'Simulated Annealing' algorithm.

In the 1950s Metropolis and his colleagues had already added a new condition for accepting random moves in the simulation of solids to thermal equilibrium, finding not all random moves were always feasible in the search space involving interaction of energies between two atoms (Luke, 2002). Hence, a condition was introduced to prevent the acceptance of all the random moves. This condition is known as the Metropolis criterion and the algorithm is known as Metropolis' Monte Carlo Simulation or simply Metropolis' algorithm (van Laarhoven and Aarts, 1987). After incorporating the Metropolis Criterion, the simulation procedure becomes as follows. Every random move brings a small random change in the current state i with energy E_i to a new configuration j with energy E_j and then, compares the energies. If the configuration j has equal or less energy ($E_j \leq E_i$) than the initial configuration i, the new state j is accepted. If the E_j is higher than the E_i, the acceptance is probabilistically determined by comparing the value of the Metropolis criterion with uniformly distributed random numbers between 0 and 1. The Metropolis criterion is as below (Equation 3.3):

$$P(\Delta E) \approx \exp^{(-\Delta E/T)} \qquad \text{Equation 3.3}$$

where T is the temperature.

The algorithm generates a large number of transitions at each temperature step, thus the system attains a thermal equilibrium with probability distribution of the states corresponding to the Boltzmann distribution (van Laarhoven and Aarts, 1987). In 1983, Kirkpatrick and his colleagues found similarities between the process of finding the lowest energy state of a system and the combinatorial optimisation aimed at the minimization of the cost function (Kirkpatrick *et al.*, 1983). In the iterative improvement method of combinatorial optimisation, the cost function acts as the energy of the system and accepts only the lower cost function that is always moving down the slope, until there is no improvement in the cost function. This system finally ends up with a local optimum solution. A rapid reduction in temperature from a high temperature to a freezing temperature does not yield a solution close to an optimum solution. However, the application of the Metropolis algorithms in combinatorial optimisation problems enables acceptance of even the higher cost function probabilistically and searches for the global optimum, where the configuration of the problem, the cost function and control parameter replace the state of the solid, the energy and the temperature, respectively (van Laarhoven and Aarts, 1987).

The Simulated Annealing algorithm is, in fact, an application of Metropolis' algorithm, applying a procedure in statistical mechanics to the field of combinatorial optimisation. The procedure, in this case, begins with an initial configuration i of the problem having initial cost function F_i at a very high control parameter (C). A small random change in the original configuration i is brought about by a predetermined procedure to generate a new configuration j with cost function F_j. If the $F_i > F_j$, the new configuration j is automatically accepted, whereas if $F_i < F_j$, the new configuration is accepted with a probability value of the Metropolis criterion given by: $\exp (- (F_i - F_j) / C)$. Unlike the iterative improvement method, the uphill moves, that is, the higher cost functions, are also accepted, when the value of Metropolis Criterion is greater than the uniformly distributed random number between 0 and 1. If the random number value is higher, the new configuration is rejected and the current configuration is used for further simulation. The process is repeated until there is no further deterioration in the cost function, implying the attainment of an equilibrium at the specified control parameter. The whole process is the same as in Metropolis' algorithm.

When equilibrium is reached, the control parameter is reduced by a very small amount and the same algorithm is repeated. This process is continued until the value of the control parameter comes down to a small value and no further change in the cost function is expected. At this stage, the simulation is stopped and the frozen configuration with the cost function is regarded as the final solution offered by the Annealing algorithms. Figure 3.1 summarizes the steps of Simulated Annealing algorithms.

Simulated Annealing is a stochastic search method based on randomization techniques (Yao, 1995). Its basic foundation lies in *iterative improvement algorithms* or *neighbourhood search* or *local search*, where the algorithm terminates in a local minimum, based on the initial configuration (van Laarhoven and Aarts, 1987; Aarts and Korst, 1989). However, unlike the iterative improvement algorithms or gradient methods, Simulated Annealing yields a solution that is not dependent on the initial configuration and the solution is very close to the global solution (Mundim *et al.*, 2003). The wider application of the Simulated Annealing algorithm to solving large scale combinatorial optimisation problems is associated with its ability to find a global optimum embedded in several local minima through the occasional acceptance of uphill moves (NRC, 1992)). It has successfully delivered acceptable solutions to classic combinatorial optimisation problems like Travelling Salesman Problems (TSP), circuit design (Kirkpatrick *et al.*, 1983), graph partitioning (Johnson *et al.*, 1989), job shop scheduling (van Laarhoven *et al.*, 1992), server allocation (Liu *et al.*, 1994) and most important for this research, land resource allocation (Aerts, 2002; Aerts and Heuvelink, 2002).

Begin

1) Initial feasible solution
   with initial temperature (T_1) and cooling function
   current cost function (F_i)

2) Temperature step N = 1

   I. Search for new solution with cost function (F_j)

   II. Compare (F_i) and (F_j)

   III. Accept the new solution if (F_i) > (F_j)
   or
   If (F_i) < (F_j) use Metropolis criterion.

3) Repeat steps I-III for specified number of iteration in $K_1 = 1$

4) Reduce initial temperature by using cooling rate

5) Start from step 2 with next temperature step N + 1

6) Terminate if stopping criterions is met.

End

Figure 3.1 A simple procedure of Simulated Annealing

3.2.1.1 Parameters for implementing Simulated Annealing Algorithm

In order to be able to implement Simulated Annealing to address optimisation problems, the configuration space, new solution generation mechanisms, the cost function and a cooling schedule have to be decided (Sundermann, 1996). Besides these points, Pirlot (1996) also found the choice of stopping rule an important parameter for the Simulated Annealing optimisation. These are the major elements of a Simulated Annealing algorithm and are described below.

1. Configuration Space

The configuration space is the main functional area where the algorithms operate to generate the optimum solution. It comprises all the elements of a control variable; therefore, the representation of a configuration space is dependent on the problem type. In the Travelling Salesman Problem, the cities to be visited are represented by an integer number from 1 to N and the configuration is found by the permutation of these integers (CUP, 1992). Grid cells have been used for spatial representation of the logging area in harvest scheduling problems (Boston and Bettinger, 1999) and land allocation problem (Aerts, 2002) and by pixel intensities in phantom images (Sundermann, 1996). The type of problem itself and the decision variables determine the representation of the configuration space.

2. New configuration generation

The algorithm searches for an optimum solution starting with an initial solution or configuration. A transition to this initial configuration is made to create a new configuration through applying a predetermined procedure. The successive generation of new solutions is a prerequisite for reaching the final solution. This involves a small change in the original configuration (van Laarhoven and Aarts, 1987) and is called a neighbourhood solution. The searching strategy should ensure that it reaches all feasible solutions (CSEP, 1996) to be able to find a global optimum solution. A new solution is generated from the current solution by bringing a small change in it (Tuyttens *et al.*, 2000) and this process is repeated until the stoping rule is met. Insertion, interchange and one position random change are different techniques for creating the neighbourhood solution (Kim and Kim, 1996). Some mathematical equations have also been used for generating new solutions from the neighbourhood solutions (Vanderbolt and G., 1984; Parks, 1990). Aerts (2002) applied an interchange or swap method in solving a MOLAA problem as it does not bring about any change in the number of cells allocated to each land use type. However, each neighbourhood solution may or may not improve the cost function. This process may play a crucial role in finding the global solution and also in determining the computational efficiency.

3. Cost function

The goal in using the Simulated Annealing algorithm is to improve the cost function most closely approaching the global optimum. In a combinatorial optimisation problem, the objective function has been called the cost function, which is to be minimized or maximized. The cost function is assessed after each move and the decision to accept or reject is made based on the cost function values and the Metropolis criterion. The objective function or cost function for some classical combinatorial optimisation problems are given below.

In Travel Salesman Problem, the objective function (F) for N numbers of cities represented by coordinates (x_i, y_i) is given below (see CUP, 1992):

$$Minimize \quad F = \sum_{i=1}^{N} \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2} \qquad \text{Equation 3.4}$$

In a Positron Emission Tomography (PET) image reconstruction problem, Sundermann (1996) changed the classical cost function by introducing the logarithm of the likelihood and removing the constant term; it becomes as in Equation 3.5.

$$Minimize \quad F = \sum_{i,j} P_{ij}^{i} \ln P_{ij}^{p} - P_{ij}^{p} \qquad \text{Equation 3.5}$$

4. Cooling schedule

In the Metropolis algorithm, the molten solid is cooled down by successive lowering of the temperature until it reaches a ground state. This process of cooling is described as the cooling schedule. Based on how slowly the temperature is reduced, the cooling schedule can be annealing or quenching (Kirkpatrick *et al.*, 1983). The cooling schedule is critical to the performance of Simulated Annealing as it determines the degree of uphill movement permitted during the search and is therefore crucial for the overall performance of the algorithm (CSEP, 1996). To describe a cooling schedule, one must decide on the initial temperature, the cooling function and number of iterations per temperature step.

I. Initial temperature

The value of temperature or the control parameter determines the rate of acceptance of the deteriorated cost function in Simulated Annealing (Pirlot, 1996). At the high initial value of temperature, the value of the Metropolis criterion tends to be near to one and all the higher cost functions will be accepted. As the temperature goes on decreasing, the chances of uphill moves by selecting a higher cost function will diminish gradually and only the lower cost functions are selected.

In order to escape from the local minimum through accepting even the deteriorated cost function, the initial temperature should be quite high. There is no obvious rule for determining the initial temperature. However, van Laarhoven and Aarts (1987) suggested that the initial temperature should be able to accept about 80 percent of all the higher cost functions and is possibly determined by random trial with different temperatures. The range and distribution of the decision variable determine the initial temperature or control parameter. A method has been proposed by Sundermann (1996) to estimate the initial temperature that allows acceptance of about 82% of non-improving cost function from only one trial run.

II. Cooling function

The initial temperature or the control parameter should be decreased after reaching a steady state or the thermal equilibrium. In the annealing schedule, the rate should be very slow and there should be enough transition to reach thermal equilibrium. Kirkpatrick *et al.* (1983) used an exponential cooling scheme for decreasing the temperature by 90 percent. This cooling rate is simply found by multiplying the temperature (T_i) by a constant factor (r), as given by the equation below.

$$T_{i+1} = r * T_i \qquad \text{Equation 3.6}$$

The value of the constant factor should be greater than zero and less than one and is determined iteratively for each problem. Van Laarhoven and Aarts (1987) suggested the best value of r is in between 0.8 and 0.98. Sarkar and Newton (2001) claimed that the performance should not be sensitive to the r value in robust Simulated Annealing.

Randelman and Grest (1986) used a linear cooling scheme, where the temperature is decreased by the ΔT after a defined number of iterations (L), as given by Equation 3.7.

$$T_{i+1} = T_i - \Delta T \qquad \text{Equation 3.7}$$

The rate of cooling is vital to improving the quality of a solution. The slower cooling rate requires more computational time but yields a better solution than the faster rate (Randelman and Grest, 1986). In theory, the temperature should decrease at the logarithmic cooling rate. However, the geometric schedule has wider application in the algorithm implementation, giving a better result with much less computational effort (Hajek, 1988; Pirlot, 1996).

Other cooling functions available to freeze the system after starting at a very high value are as by Equations 3.8 and 3.9 (Luke, 2002).

$$T_{i+1} = T_o - i\,(T_o - T_n)\,/\,N \qquad \text{Equation 3.8}$$

$$T_i = T_o - I^A \qquad \text{Equation 3.9}$$

where T_i is the control parameter at i th steps and r is a constant factor for reducing the control parameter. T_o is the initial control parameter. N is the number of control parameter steps. T_n is the final value of the control parameter. A is a function of $A = LN(T_o - T_n)/LN(N)$.

Figure 3.2 illustrates the cooling of the initial control parameter (2000) by different cooling functions against the number of cooling steps. The final temperature 0.043029 was reached after 103 temperature steps by the cooling function given by the equation 3.6. The initial control parameter dropped very quickly in the first quarter of the cooling steps. This cooling function reduced about 86 percent of the initial value in 20 steps and then the value decreased slowly. The cooling function (Equation 3.7) reduced the initial value linearly and decreased it to about half (1000) in 51 steps. The cooling function as given by equation 3.9 happened to be the slowest cooling rate in the first half of the steps and reduced the initial value to 1368 in 51 steps.

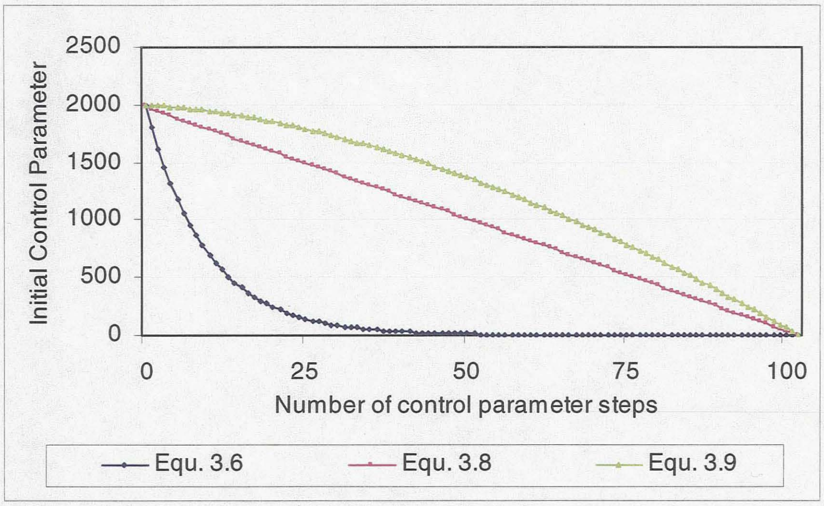


Figure 3.2 Cooling of initial control parameter by different cooling functions

III. Iterations per control parameter (temperature) step

The number of iterations per control parameter (temperature) step should be enough for the system to reach a steady state (Kirkpatrick *et al.*, 1983; Sundermann, 1996) and is called the epoch length (Kim and Kim, 1996). The number of iterations per control parameter (temperature) step is generally dependent on the size of the problem and is independent of the number of temperature steps (CSEP, 1996). A new criterion such as a minimum number of transitions to be accepted at each temperature step may also be used as an alternative to the specified number of iterations per control parameter (temperature) step. When either of these conditions is met, the iteration is stopped (CSEP, 1996).

5. Stopping rule

The main aim of the algorithm is to find an optimum solution. As soon as the optimum solution is reached, the algorithm has to be stopped. The point at which it will be stopped can be assessed by the situation, that is, when there is no further improvement in the cost function throughout a temperature step (CSEP, 1996). Pirlot (1996) has explicitly defined this criterion in two ways: a) if the cost function is not better off by a defined percentage (ϵ_1 %) even after a certain number of transitions (K_1); or b) if the cost function is not accepted for specified percentage (ϵ_2 %) of the iteration (L) for the transition (K_2). The values of ϵ_1 and ϵ_2 can range from one to five percent.

Another stopping rule may be a threshold on the computation time to terminate the algorithm after reaching the specified computation time (Kim and Kim, 1996). The final temperature value can also be a stopping criterion in some cooling functions. If the minimum temperature is prescribed in the algorithm, obviously the algorithm is stopped at that point. The total number of solutions to be generated can also be prescribed as the stopping criterion in the algorithm (CSEP, 1996).

In problems where multiple local minimum situations exist, it is often difficult to find the global optimum by other optimisation techniques like Newton's method, the Simplex method or the Least-squares method, unless the search is started quite close to the global minimum. These methods follow the search only in the local gradient towards the minimum and therefore, are not able to look for a global minimum located somewhere else (CSEP, 1996). Kirkpatrick *et al.* (1983) described the Simulated Annealing algorithm as a global optimisation technique applicable even in problems with several local minimums. The major advantage of Simulated Annealing in the optimisation is the chance of escaping from the local minimum through accepting the new state with a higher energy level. Although there is a temporary rise in the objective function, the move enables the gradient to be overcome and thus escape a local minimum. It means that the problem of convergence at the local minimum is overcome by probabilistically accepting the move with higher energy. This algorithm has wider application and scope for many instances of combinatorial optimisation problems and therefore, has been categorically defined as a general approximation algorithm.

3.2.1.2 Applying Simulated Annealing to a MOLAA problem

The application of the Simulated Annealing algorithm to a land allocation problem has already been shown to be effective (see Aerts, 2002; Aerts and Heuvelink, 2002). The allocation of three land use types (forest, water and shrubs) was demonstrated in a case study of the As Pontes mining area in Spain. The aim of the optimisation was to minimize the development cost (C_{ijk}) by allocating these land uses to a desired percentage of the area. The cost function based on development cost only was given by Equation 3.10.

$$\textit{Minimize} \quad \mathrm{F} = \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=0}^{M} C_{ijk} x_{ijk} \qquad \text{Equation 3.10}$$

Where x_{ijk} is the binary variable and becomes 1 when cell ij is assigned with land use k and zero otherwise. Aerts (2002) estimated the cost value for each pixel using only two land attributes (elevation and slope) for three land use types (forestry, shrubs and water). The cost in dollars was estimated by using Equation 3.11.

$$C_K = a_k \text{ x elevation} + b_k \text{ x slope} \qquad \text{Equation 3.11}$$

Where C_K is the cost for land use k; a_k and b_k are parameters specific to the land use type. Aerts (2002) applied values between 1 and 1.5 for elevation and between 1.5 and 3.0 for slope.

The spatial compactness function was added in the previous development cost model to enhance compactness by rewarding the allocation of the same land use type in the four neighbourhoods by using a compactness factor (β). Then, the objective function became as below (Equation 3.12):

$$Minimize \quad F = \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M} C_{ijk}x_{ijk} - \beta\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M} b_{ijk}x_{ijk} \qquad \text{Equation 3.12}$$

In applying the algorithm to this problem, the initial temperature was found by iterative searching of 80 percent acceptance of the higher cost function. The temperature was reduced by 80 percent after completion of 1000 iterations at every temperature stage. The initial solution was obtained by random allocation of land uses satisfying the desired percentage of areas. The compactness factor (β) with value 3 was found to be an appropriate trade-off between the development cost and the compactness. The algorithm was implemented following a simple procedure of Simulated Annealing (see Figure 3.1). A diagrammatic representation of the use of Simulated Annealing in solving a MOLAA problem is shown in Figure 3.3. Every iteration produced a new solution by swapping land uses between two randomly selected cells. The new cost function was assessed to accept or reject the new solution as determined by the Metropolis criterion. The algorithm was stopped when there was no more improvement in the cost function. This case study revealed a realistic solution to the problem and also demonstrated that Simulated Annealing could handle large size land allocation problems on a grid of 525 by 525 cells.

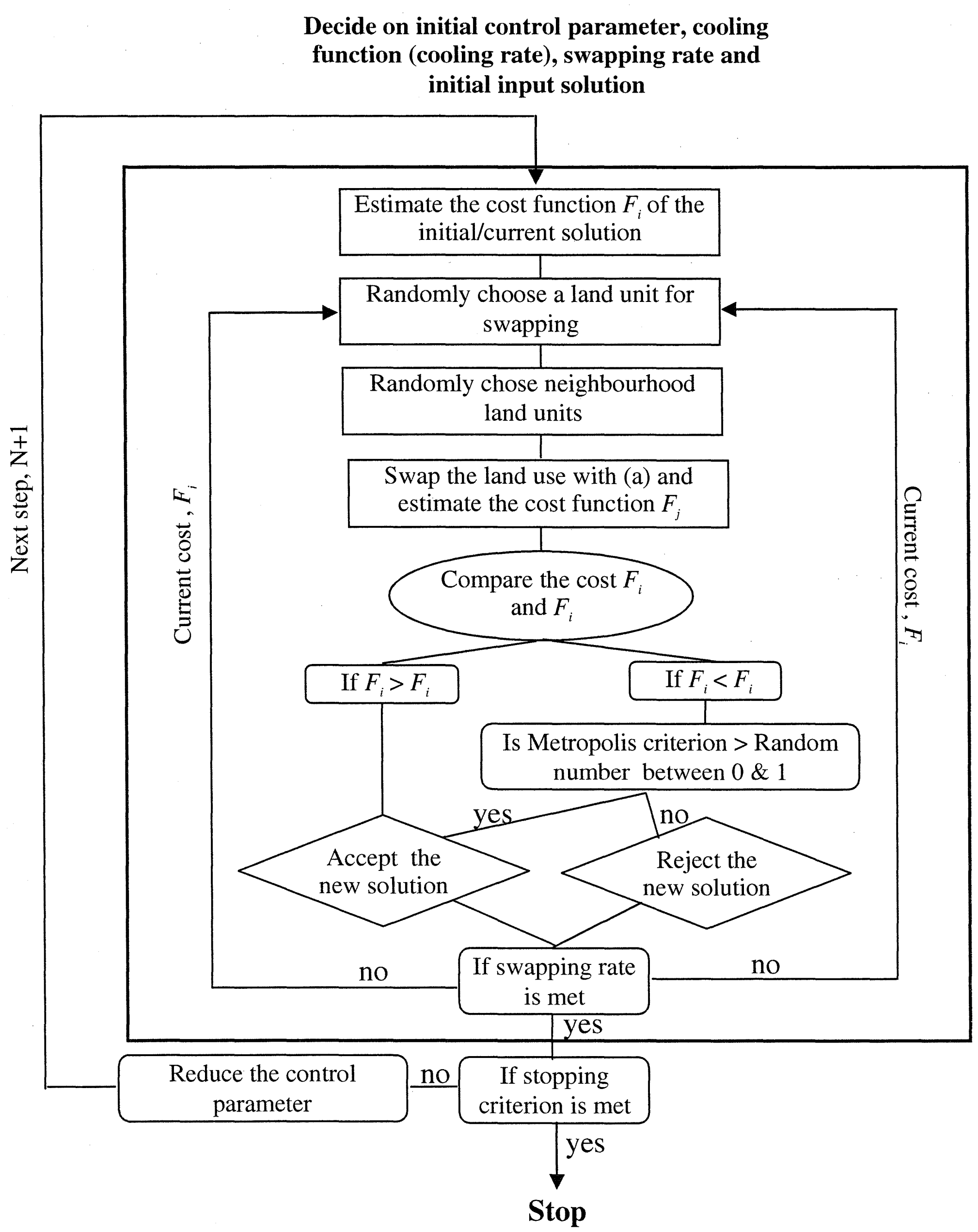


Figure 3.3 Flow chart for Simulated Annealing algorithm in solving a MOLAA problem

3.2.2 Tabu Search algorithm

Tabu Search (TS) evolved from a local search method by incorporating a new strategy of preventing the algorithm to be trapped at a local minimum (Voudouris, 1997). This algorithm was independently developed to solve combinatorial optimisation problems by F. Glover and P. Hansen and applied to nonlinear covering problems and maximum satisfiability problems, respectively (Glover, 1989). The algorithm follows an iterative process and tries to improve the solution by searching for a better solution from the neighbourhood. The strategy relies on some long-term or short-term memory structure to restrict cycling of the search without improvement in the objective function and also helps to avoid local minima. The conditions unique to a problem are set out and stored in these memories. A solution in the neighbourhood qualifies as a potential move, if the conditions are met; otherwise, the move is restricted (Cvijovic and Klinowski, 1995). Those 'forbidden' moves are regarded as 'Tabu', signifying 'sacred' in some Pacific Island languages or forbidden in a general sense (Glover and Laguna, 1997). It is similar to Simulated Annealing, in that it also uses a guided procedure to accept a worse solution in order to escape from being trapped at the local minimum (Glover *et al.*, 1993). Continuous advancements in this technique have made it efficient and widely applicable to combinatorial optimisation problems in many fields (Glover, 1989; Glover *et al.*, 1993). This algorithm has been successfully applied to forest harvest scheduling (Richards and Gunn, 2000), quadratic assignment problems (Heffley, 1972; Taillard, 1991) multiple minima problems (Cvijovic and Klinowski, 1995) and continuous optimisation problems (Chelouah and Siarry, 2000).

A simple procedure for Tabu Search is widely described in the literature (Glover, 1989; Glover *et al.*, 1993; Cvijovic and Klinowski, 1995; Pirlot, 1996). The algorithm starts with an initial solution x_1 in X and searches for the best solution x^* within the neighbourhood $V(x)$. The cost function F^* and the solution x^* are both accepted. If none of the moves in the neighbourhood are better than the current solution x_n, the solution x which least degrades the solution, is accepted in the neighbourhood $V(x)$. This strategy enables the local minimum situation to be overcome. If the solutions x and x_n are members of same neighbourhood structure $V(x)$ or $V(x_n)$, it is likely that the search process may cycle between x and x_n solutions repeatedly. The essence of a Tabu Search is that it avoids this cycling by creating a short memory called a Tabu list, where the attribute of solution x is stored. The Tabu list stores a specified number of solutions (L) and restricts acceptance of these items unless they are released from the list. However, the algorithm uses aspiration level in order to release the restriction posed by the Tabu list to the 'good enough solution'. The search process proceeds until the stopping condition is encountered. Figure 3.4 summaries a simple procedure of Tabu Search as given by Glover *et al.* (1993). Several researchers have shown the benefits of Tabu Search over Simulated Annealing in terms of computation time and quality of the solution for various combinatorial optimisation problems.

Begin

1) Initial feasible solution
define Tabu move and Tabu length (T_L)
current cost function (F_i)

2) Iteration step $N = 1$

I. Search for new solution in the neighbourhood with cost function (F^*)

II. Compare the neighbourhood and select the best with (F_j)

III. Accept the new solution if (F_i) > (F_j)
or
If (F_i) < (F_j) apply criterion for acceptance or rejection.

3) Repeat steps I-III for specified number of iteration in $N = 1$

4) Start from step 2 with next iteration step $N + 1$

5) Terminate if stopping criterions is met.

End

Figure 3.4 A simple procedure for Tabu Search algorithm

3.2.2.1 Elements of Tabu Search

Tabu Search shares the same description as for the Simulated Annealing for the configuration space, the neighbourhood structure, a new solution generation mechanism and the objective function or cost function, as discussed in section 3.2.1.1. The following sections describe unique elements of Tabu Search.

1. Defining neighborhood

In optimisation, the search proceeds with finding a solution in a neighbourhood (N_s). A neighbourhood of solution s comprises those solutions in the whole set of solution S that can be reached in a single move (Cvijović and Klinowski, 1995). The move restricts a search within the subset specified by N_s. The combinatorial problem and the search method define a neighbourhood structure (Voudouris, 1997). The neighbourhood is defined as a set of moves or search methods to generate a new solution from a current solution (Taillard, 1991). The algorithm tends to choose the best solution from its neighbouring solutions. This is a "greedy" search strategy and leads to a local minimum, where none of the neighbours improve the cost function. To escape from the local minimum situation, Tabu Search also accepts a move which increases the cost function (Taillard, 1991).

2. Tabu list, Tabu length and Tabu state

The unique feature of this algorithm is a specified condition or constraint to guide the search process. This condition enables the cycling or reverse moves to be restricted by using short and long-term memory. It relies on memory by storing the solutions or their attributes in a list. These solutions are inaccessible for a specified number of iterations and are regarded as the Tabu moves. The list is called a Tabu list. The number of solutions stored in the list defines the Tabu length (L). A complete description of these solutions may be stored in the memory. However, it is more appropriate to use an attribute of the solution visited in the last L iteration (Glover *et al.*, 1993; Pirlot, 1996). The choice of an attribute for a Tabu list is specific to a problem (Glover *et al.*, 1993). A different Tabu condition may be used for the same attribute to determine the severity of the restriction by the Tabu move (Glover, 1989). Taillard (1991) defined a Tabu move by restricting any transfer between units to locations already exchanged within a specified number of latest iterations in a quadratic assignment problem.

Tabu length (L) determines the number of elements in the Tabu list. A constant or variable list size may be used (Cvijović and Klinowski, 1995). However, an appropriate Tabu length should be used for efficient performance of the algorithm. Neither a very small nor a very large Tabu length is desirable. The former leads to cycling of the move and the latter may be very restrictive even to good solutions (Taillard, 1991). Taillard suggested using variable Tabu length by randomly selecting a number between the defined minimum and maximum length.

Glover (1989) introduced an array called Tabu state to simplify the implementation of Tabu condition. The items with the same attribute value (e.g. weight) are recorded in a matrix of frequency (n) and weight (r) in the Tabu state. If a weight (w_q) is restricted, it is assigned a value of one and the rest assigned zero in the Tabu state. In an optimal partition problem, the Tabu list (T) records two ordered pairs for each solution in a circular pattern unless the specified Tabu length (L) is occupied. Once the Tabu length is reached, the Tabu list is made empty and released from the Tabu state. The Tabu list and Tabu state repeat the same process (Glover, 1989). It is more appropriate to use multiples of Tabu lists in this algorithm (Glover *et al.*, 1993). One of the main aims of the Tabu list is to diversify the search by enabling the current solution in the space not visited before to be reached (Pirlot, 1996).

3. Aspiration level

A Tabu list may operate in a very restrictive way and may also prevent acceptance of many good solutions (Taillard, 1991). A condition is used to release such good moves temporarily from the Tabu list to allow their acceptance. This rule is called the 'aspiration level' in Tabu Search. The aim of defining aspiration level is to allow selective acceptance of promising solutions, which have been restricted by the Tabu list (Glover, 1989). A condition may arise where a Tabu move (m) is able to approach a better solution than the best solution attained so far. In this situation, it is necessary to accept the Tabu move (m) in order to improve the solution. Hence, the Tabu restriction can be released if the m meets the aspiration level.

3.2.2.2 Applying of Tabu Search to a MOLAA problem

A diagrammatic representation of Tabu Search in solving a MOLAA problem is shown in Figure 3.5. To apply Tabu Search in solving a MOLAA problem, a land unit is selected in the initial solution. The neighbours of the land unit are also selected and assessed in terms of the cost. Subsequently, the land uses are swapped between the selected land unit and its best neighbour in a way that minimizes the cost function among all the neighbours. This swapping operation produces a new solution. The location attributes of both land units are stored in the Tabu list to avoid cycling or reversing the move for the specified length of Tabu size. All subsequent moves are stored in the Tabu list unless the Tabu length is reached. When the iteration becomes equal to the Tabu length, the list is updated by replacing the first Tabu list. The algorithm is stopped when there is no improvement in the cost function throughout an iteration period. Details of the parameters used for applying Tabu Search to a MOLAA problem will be described in Chapter 5.

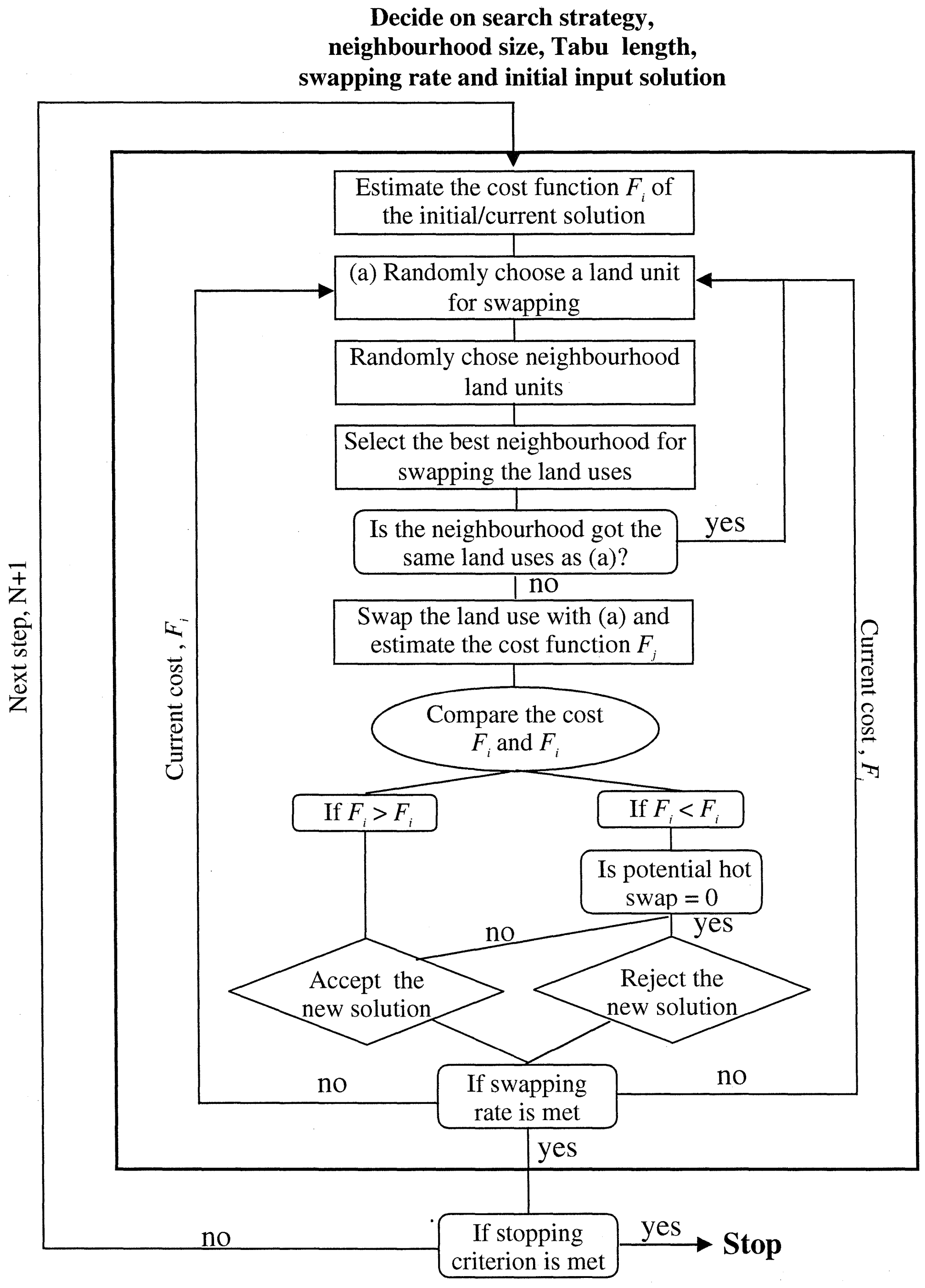


Figure 3.5 Flow chart for Tabu Search in solving a MOLAA problem

3.3 Multi objective land use allocation (MOLA)

MOLA is a GIS based decision support module devised to provide a solution to multiple and conflicting land use allocations. This module is based on **choice heuristics** and uses the same decision rule to solve a single land use allocation. This module uses an iterative process and relies on the same decision rule that is employed to solve a single land use allocation problem (Eastman *et al.*, 1993). Eastman (2001) has elaborated the procedure as follows (Figure 3.6): A suitability map scaled in a range of

0 - 255 is derived for each land use combining several criteria with their relative weights using a multi-criteria evaluation (MCE) module (Step a). The WEIGHT module estimates the relative weight of each criterion by pair-wise comparison. The RANK module is used to generate a rank map in ascending or descending order from each land use suitability map by assigning 1 either to the lowest value (0) or highest value (255) (Step b). This module gives rank order based on the values in the suitability map. The cells with the same suitability values are randomly assigned a rank order. Finally, the MOLA module performs iterative operations to combine the rank maps based on their specified weights. A land use allocation map, satisfying area requirement for each land use type is then generated (Step c). A secondary image may be used to prioritise the rank maps for resolving land use conflicts in the module.

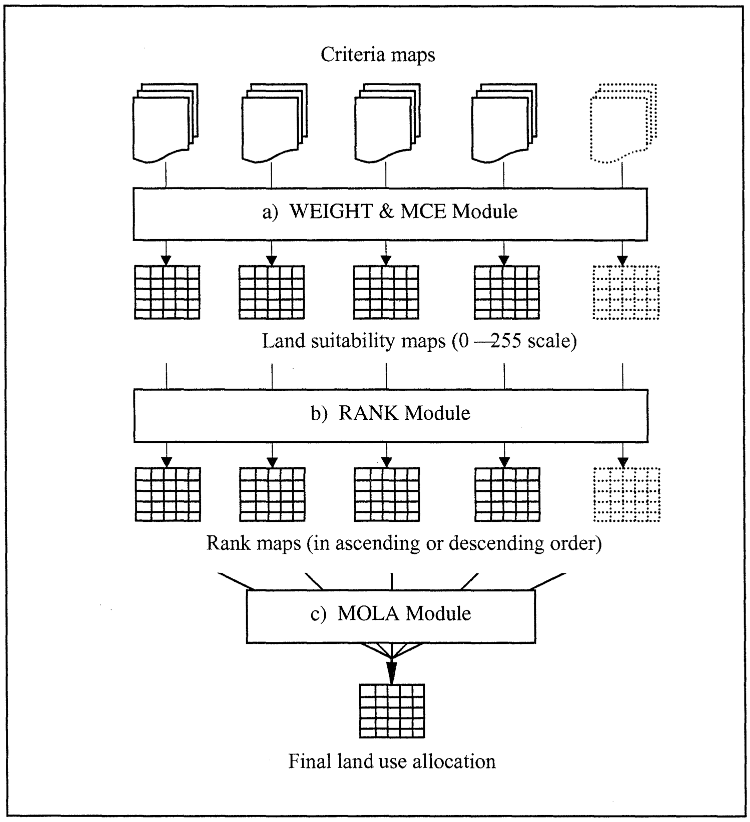


Figure 3.6 MOLA procedure in IDRISI® Software

The MOLA resolves land use conflict in a land unit (cell) based on its proximity to the ideal point, and assigning the cell to the land use, which has the highest-ranking weight. To facilitate the allocation of the desired number of cells to each land use type, each suitability map constitutes an axis in a multi-dimensional decision space. For instance, the decision space for two land uses, agriculture and conservation is shown in Figure 3.7a. The area requirement for both land uses can be achieved by selecting the most suitable land units for the respective land use by moving the decision line towards the origin (0) as in Figure 3.7b. However, the cells in the upper right corner where the decision lines overlap, are suitable for both land uses and represent the area of competition or conflict. To resolve this conflict, each cell is allocated to that land use which has the highest suitability value close to the ideal point. The ideal point is the extreme value in the axis, that is, 255 for both land uses. Different weight scenarios for the rank maps are taken into account by separating the region of conflict with a line originating from the meeting point of two decision lines. The angle of the line is proportional to the weighting of the land use. For land uses having the same weight, the angle of separation will be 45 degrees (Figure 3.7b). Conflict resolution is carried out in several iterations to achieve the area required for each land use.

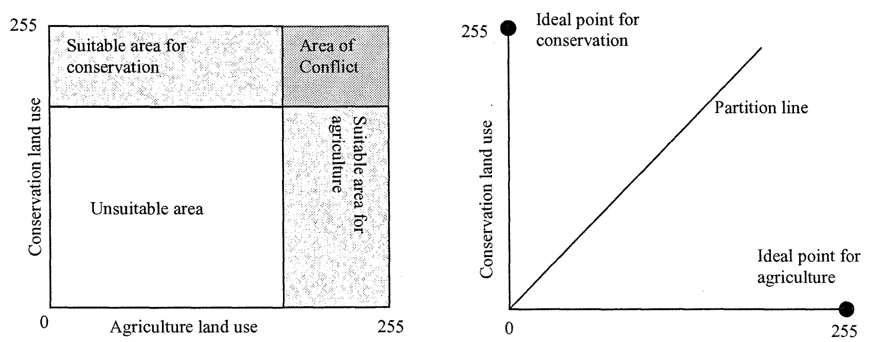


Figure 3.7 Decision space for MOLA (a) and Conflict resolution rule in MOLA (b)

3.4 Summary

This chapter has discussed two combinatory methods and the GIS based MOLA module available in IDRISI software. These methods will be applied in solving the same MOLAA problem. Their performance will be compared by assessing the quality of the solution and its efficiency. Both the combinatory methods are widely applied in solving combinatory optimisation problems because of their ability to generate a sub-optimal solution in an acceptable time frame. The sub-optimal solutions tend to be close to the optimal solution and also superior to the solutions arrived at by local optimisation methods. The superiority of the solution is mainly attributed to their strategy to escape from the local minima, even while accepting a higher cost function. In Simulated Annealing, the Metropolis Criterion determines the acceptance of the higher cost function whereas in Tabu Search, the short term and long term memory and the stated condition restrict the cycling of the move and also avoid being trapped in the local minima. These methods were also discussed in the context of their application to a MOLAA problem.

The MOLA module in IDRISI was also described in detail, illustrating the decision space and decision rule for conflict resolution between multiple land uses. A research framework for applying these methods to the same MOLAA problem will be described in the next chapter. Chapter 4 describes the detailed implementation of these methods after designing the MOLAA problem.

Chapter 4

RESEARCH FRAMEWORK AND STUDY SITE

4.1 Introduction

This chapter will focus on the research framework which provides the research direction to this study in order to achieve the objectives stated in Chapter 1. The framework constitutes several sequential steps that are discussed here. The research site and the datasets used for this research will also be discussed in this chapter.

4.2 Research framework

Besides the optimisation methods, the land use suitability models, the parameters specific to the combinatorial methods and also the generation of initial solutions may influence the optimisation process and the solutions reached from the combinatory methods. All these elements have been taken into account in designing the framework for this research, as illustrated in Figure 4.1. This research framework is based on the land use decision-making framework discussed in Chapter 2. Each of these steps is described briefly in the following paragraphs and the details of the actual procedure will be discussed in Chapter 5.

1. Identify the stakeholders

The initial step is to identify the stakeholders, that is, those who have an interest in and would like to take part and contribute to land use planning processes in the region. It includes the local people, communities, interest groups or lobby groups and government institutions. This research applies to a hypothetical land use allocation problem in the Kioloa region. Therefore, stakeholders are not actually considered in this research.

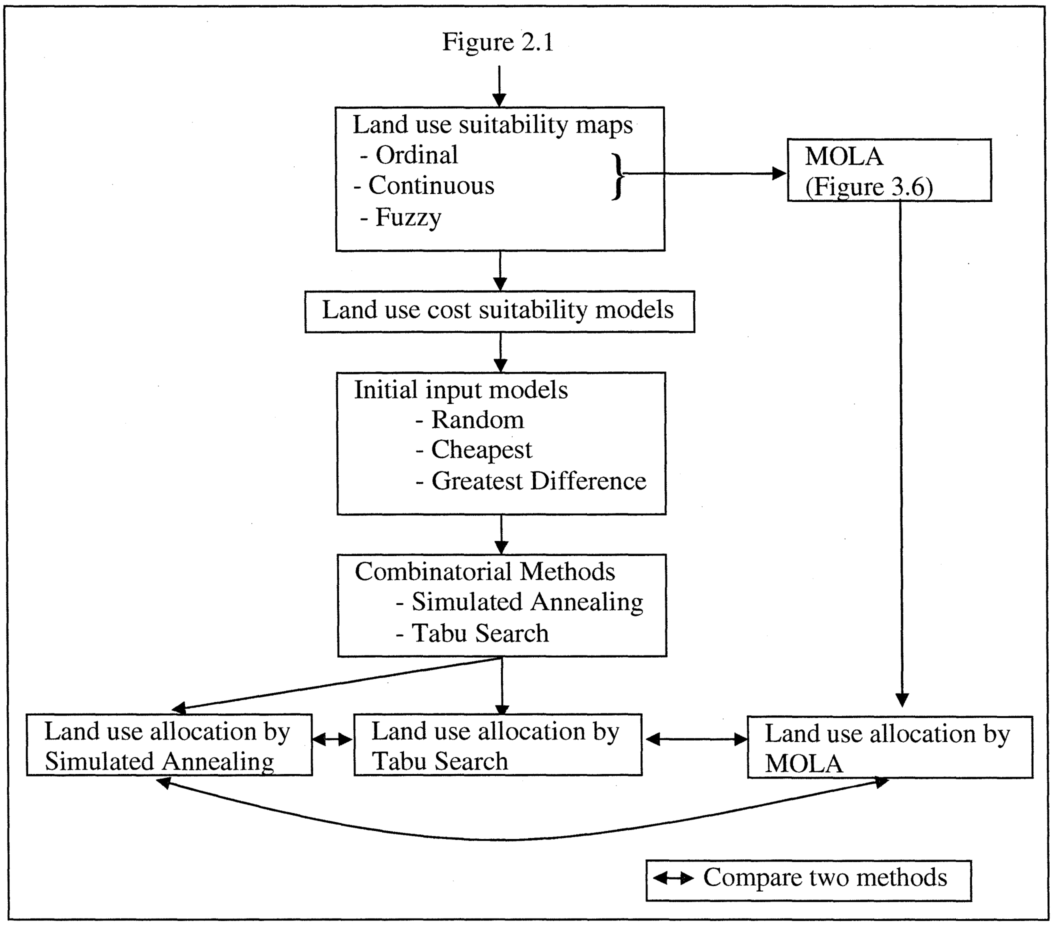


Figure 4.1 Research framework for comparing three different methods for solving a MOLAA problem

2. Land use issues and objectives

In the Kioloa region, different social, economic and environmental issues relating to land resource were considered in order to specify the land use objectives for the area. The land use issues and objectives are discussed in the process of designing a hypothetical MOLAA problem in the Kioloa region.

3. Land use types and area requirement

The land resource should be used to mitigate the land use issues or to derive land use objectives. These land use issues and objectives were translated into one or more land use types for both problems. After deciding on the land use types, one key question was to decide on the area to be allocated to each land use type. For a hypothetical MOLAA problem in the Kioloa Region, the selection of land use types and their area requirement is discussed in Section 5.3.1 in Chapter 5.

4. Selection criteria and preferences

After identifying the desired land uses and the area required for each land use type, the stakeholders should provide their criteria for assessing land use suitability for the land use types. Their preferences on each criterion for a specified land use type used to combine multiple criteria into a single suitability. For the hypothetical problem, the criteria were selected based on the availability of datasets at the ANU, personal experience and the literature.

5. Land use suitability models

The classification of the attributes used for representing different criteria and also the rule of combination resulted in variations in the land use suitability models. The classical methods include ordinal and continuous classification of attributes. The Fuzzy method is now also emerging as an appropriate technique for land evaluation (Kollias and Kalivas, 1998). These methods have already discussed in Chapter 2. For assessing the appropriateness and applicability of the land use suitability model, this research uses all three land use suitability models derived by classifying all land use criteria using the ordinal, continuous and fuzzy scales. The details of attribute classification are discussed in Chapter 5. The Weighted Linear Combination (WLC) method was used to combine the criteria for each land use (discussed in the Chapter 2).

6. Applying MOLA module in IDRISI®

The land use suitability models derived by using the ordinal and continuous scale were used as input to the MOLA module in IDRISI® for allocating desired land use types by meeting the area requirements of each land use type. The results of applying MOLA to the MOLAA problem are presented in Chapter 6. The land use allocation by MOLA will be compared with the solution generated by the combinatory methods (Chapter 9).

7. Cost suitability model for combinatory methods

The combinatory methods aim to minimize the cost function in solving the MOLAA problem. Therefore, it is appropriate to use land use suitability models where the lowest value represents the highest suitability and vice versa. In the land use suitability models created in Step 5, the higher value signifies the higher suitability and the models are not appropriate to apply in the combinatory methods. Hence, these land use suitability models are transferred into cost suitability models, where the lowest value (cost) represents the highest suitability and the highest value (cost) represents the least suitability. This procedure is explained in Chapter 5.

8. Initial input solution for combinatory methods

The combinatory methods require an initial solution upon which these methods act to produce a final solution. The performance of an algorithm may be influenced by an initial input solution (Thesen, 1998). This research used three different initial input solutions generated by random, cheapest and greatest difference allocation of land uses. In the case of a MOLAA problem, an initial solution was generated by merging the cost suitability models of all land use types, meeting the specified area requirement for each type (discussed in Chapter 5).

9. Apply Simulated Annealing and Tabu Search

Although the application of Simulated Annealing to a MOLAA problem has been shown to be effective (Aerts, 2002; Aerts and Heuvelink, 2002), the paper did not discuss how one should select an annealing schedule for running the algorithm for a MOLAA problem. The annealing schedule includes an initial control parameter, a cooling function, the number of iterations per control parameter step, the length of control parameter steps and the final control parameter. These parameters were explained in Chapter 3. Among these parameters, the cooling function is the most crucial to the 'annealing' process and controls the performance of the algorithm. Three different cooling functions as given by the Equations 3.6, 3.8 and 3.9 were chosen in order to compare their influence on improvement in the cost function. The algorithm with different annealing schedules was applied as found by the combination of four values of initial control parameters, four cooling rates and four swapping rates per control parameter step to the initial solution of the ordinal, continuous and fuzzy models generated by the random, cheapest and greatest difference methods.

Likewise, the appropriate parameters for implementing Tabu Search were found by testing for different Tabu lengths, neighbourhood sizes and new solution generation techniques for improving the cost function to its minimum value. The choice of parameters for both the algorithms is described in Chapter 5. The results of applying Simulated Annealing and Tabu Search are presented in Chapters 7 and 8, respectively.

10. Compare the solution by different methods

The solutions from both algorithms were compared with the solution from the MOLA module in terms of cost minimization, the run time, spatial compactness and the input model requirement (see Chapter 9).

11. Incorporating the compactness function into the algorithms

Having the same land use type in the neighbourhood is rewarded by adding a compactness function into these algorithms, as discussed in Chapter 3. The solutions obtained after incorporating the compactness function by Simulated Annealing and Tabu Search were compared through assessing their quality in terms of the cost function and the land use compactness.

4.3 The Study site

The Kioloa region was chosen for designing a hypothetical MOLAA problem because of the availability of good digital datasets for the region at the ANU and easy access to the site (around 3.5 hours drive from Canberra). Figures 4.2 shows the location of the Kioloa Region on the map of Australia. The research will use three different problem sizes: large size grid (525 X 525 cells), medium size grid (100 X 100 cells) and small size grid (10 X 10 cells) for comparing the performance of these methods at different sizes of the planning unit. A brief description of the Kioloa region and its datasets is given in the sections that follows.

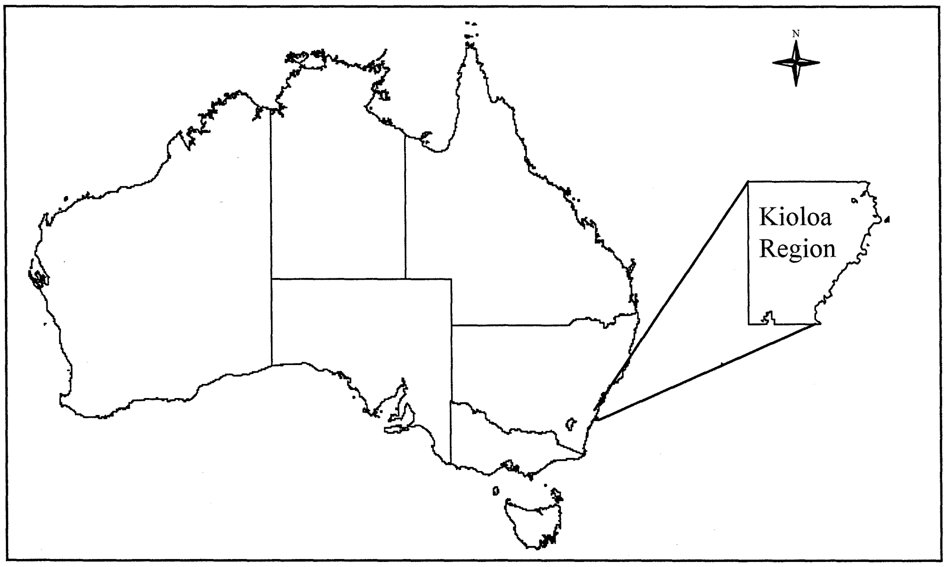


Figure 4.2 Location of the Kioloa Region on the map of Australia

4.3.1 Kioloa Region

The Kioloa region is on the South-East Coast of New South Wales, Australia and is located between S35^{0}30'00" and 35^{0}37'30" latitude and E150^{0}15'00" and 150^{0}30'00" longitude. The boundary and extent of the region are the same as for the Kioloa 8926-1N topographical map (1:25000) of Australia (LIC, 2000). The Kioloa map covers an area of 15.75 square kilometres. The entire Southeast boundary is the East coast of Australia, which abuts the Tasman Sea. Pebbly, Merry, Kioloa, Shelly, Racecourse, Murramarang, Gannet, Cormorant and Bawley are among the well-known beaches on the South Coast of New South Wales.

4.3.1.1 Land use

The Kioloa Region the region comprises both coastal areas on its Southern frontier and the mountain ranges on the North. It also includes two prominent inland water bodies - Willinga Lake and Durras Lake, located in the upper North-East and lower South-West corners, respectively. Together with the Tasman Sea, the permanent water features cover about 28.26 percent of the total area and the rest of the area is land.

Based on land uses, the region can be categorised into conservation areas, state forest, open land and residential areas. Table 4.1 gives the estimated areas of land under each land use type. State Forests covers the largest area with 38.5 percent of the total which includes seven separate Reserves or National Parks. The conservation area has the second highest area coverage with 32.31 percent of the total land. Murramarang National Park has the largest area occupying 31.8 percent of the total land. Meroo National Park together with two tiny Nature Reserves located on Belowa and Brush Islands and one Aboriginal Area comprise the rest of the conservation area. The open land and residential areas have the lowest area with only about 0.93 percent of the total land. The open land includes grassland and agricultural land in the Kioloa Region. The residential areas are mostly located adjacent to the coast.

Table 4.1 Area coverage of different land uses in the Kioloa region

S.N.	Land use type	No of cells	Area in percent
1	Water bodies (including Sea)	77896	28.26
2	Conservation Area	89068	32.31
3	State Forests	106102	38.50
4	Open land and residential area	2559	0.93

4.3.1.2 Geology

The Kioloa Region includes seven different geological types. The Ordovician rocks are the most abundant geological type. These rocks are mostly composed of shales and fine sandstones. The Permian rocks are found with sandstones and shales in some places and have been categorised into three types: Snapper Point Permian, Pebbly Beach Permian and Wasp Head Permian. These are part of the Sydney Basin formation (Lees, 2002).

4.3.1.3 Vegetation

The Kioloa region is very diverse in terms of vegetation, having about 450 species assembling into 30 forest communities and 7 forest types (Moore *et al.*, 1991). Sclerophyll forests with different eucalyptus species dominate the region. These forest types constitute Dry Scelerophyll (*Eucalyptus botryoides*), Wet Scelerophyll (*E.maculata*), Dry Maculata (*Corymbia maculata* as over storey) Wet Maculata (*Corymbia maculata; Eucalyptus pilularis*) However, a few patches of warm-temperate rain forest contribute to the vegetation diversity in Kioloa. The wide diversity and complexity of the vegetation in the Kioloa Region has been the research subject for vegetation classification (Moore *et al.*, 1991; Fitzgerald and Lees, 1994; Fitzgerald and Lees, 1996; Huang, 2003).

4.3.2 The datasets for the Kioloa Region

The major datasets for the Kioloa region include a vegetation map, a digital terrain model, a geology and map of road. These are all available at the School of Resources, Environment and Society at the Australian National University, Canberra, Australia. Table 4.2 provides a summary of the datasets and a brief description of each dataset is given in the following sections.

Table 4.2 Summary of the datasets for the Kioloa region

S.N.	Dataset	Data type	Resolution	Source
1	Vegetation map	Raster	30 X 30	(James, 2004)
2	DEM	Raster	30 X 30	(ANU, 1997a)
3	Geology	Raster	30 X 30	(ANU, 1997b)
4	Road	Vector		(ANU, 1997c)
5	Reserve Boundary	Vector		(NSWNPWS, 2004)

4.3.2.1 Vegetation map

Landsat Thematic Mapper (TM) image (2000) was used for generating a vegetation map for the Kioloa region. The image is version 6.3 and the last update was done on 4th March 2003. The image constitutes six bands: 1,2,3,4,5 & 7. The spatial resolution of each cell is 30 metres by 30 metres and matches exactly the topographical map of the Kioloa Region. A vegetation map for the Kioloa region was derived by James (2004) from unsupervised classification of Landsat image followed by field checking. Two, four and seven bands of the image were used for initial classification (James, 2004). A vegetation map derived from the false colour composite image of the region is shown in Figure 4.3.

4.3.2.2 Digital Elevation Model and its derivatives

A digital elevation model (DEM) or digital terrain model (dtm) of the Kioloa Region is available in raster format with 30 by 30 metre resolution (Figure 4.4). This model was derived by fitting the continuous surface over the contours using the interpolation technique and then changing into it a raster. Each pixel gives the actual mean height of the cell and ranges from 0 - 279 metres.

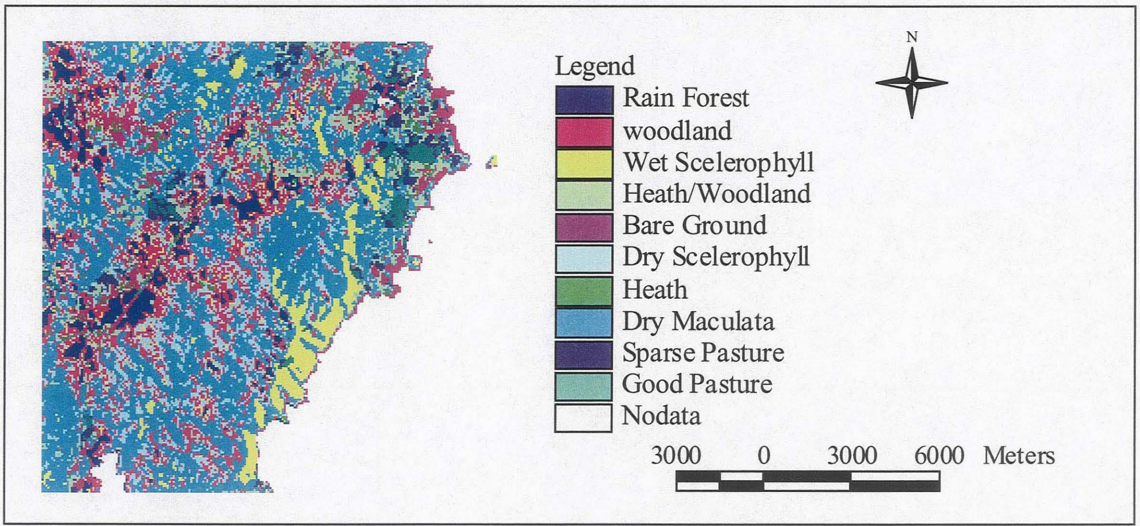


Figure 4.3 Vegetation map of the Kioloa region

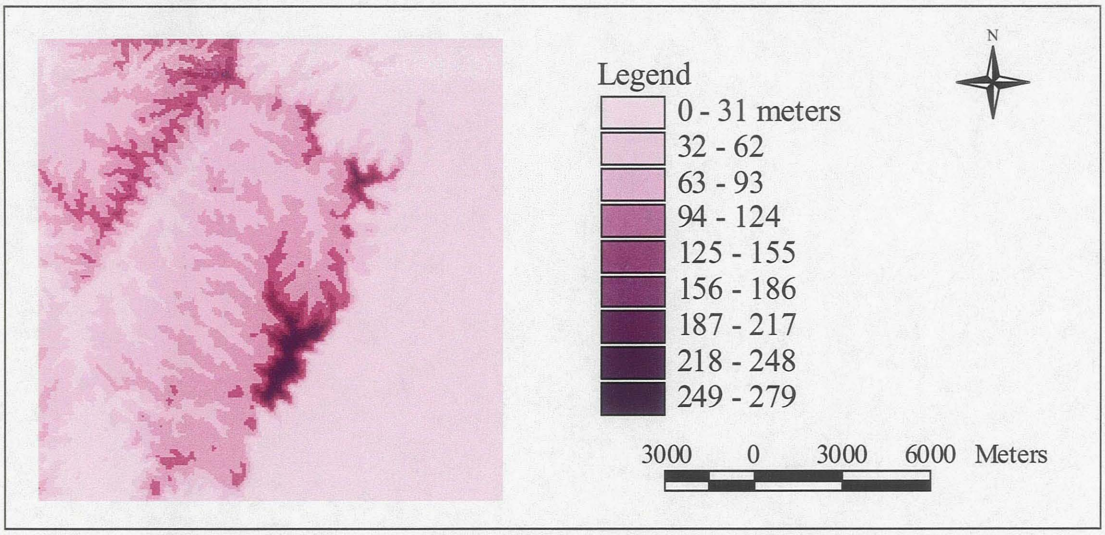


Figure 4.4 A digital elevation model of the Kioloa region

Slope, aspect and drainage network datasets were derived from the DTM using ArcInfo® for the Kioloa Region. Slopes range from 0-36.72 degrees and the higher slopes coincide with the high mountainous areas. In the aspect dataset, the plain areas are represented by -1 whereas the mountain areas get an aspect value up to 359 degrees. The stream network is based on flow direction derived from the DTM. To apply stream network as a criterion for determining the wetland, only 3 and 4 stream orders are considered and expanded to double the pixel size (60 metres).

4.3.2.3 Geology dataset

There also exits a digital dataset for the geological types of the Kioloa Region at the ANU. The major geological types of the Kioloa region have already been described above. These geological types are represented on a nominal scale (1 to 7) by assigning one class to each geological type. The frequency of each geological type is given in Table 4.3.

Table 4.3 Distribution of geology type in the Kioloa Region

S.N.	Geological type	Area (Hectares)	Area in percent
1	Quaternary Alluvium	6260	3.12
2	Tertiary Essexite	13691	6.83
3	Snapper Point Permian	37962	18.95
4	Pebbly Beach Permian	33762	16.85
5	Wasp Head Permian	6182	3.09
6	Ordovician	102503	51.16

Source: Lees (2002)

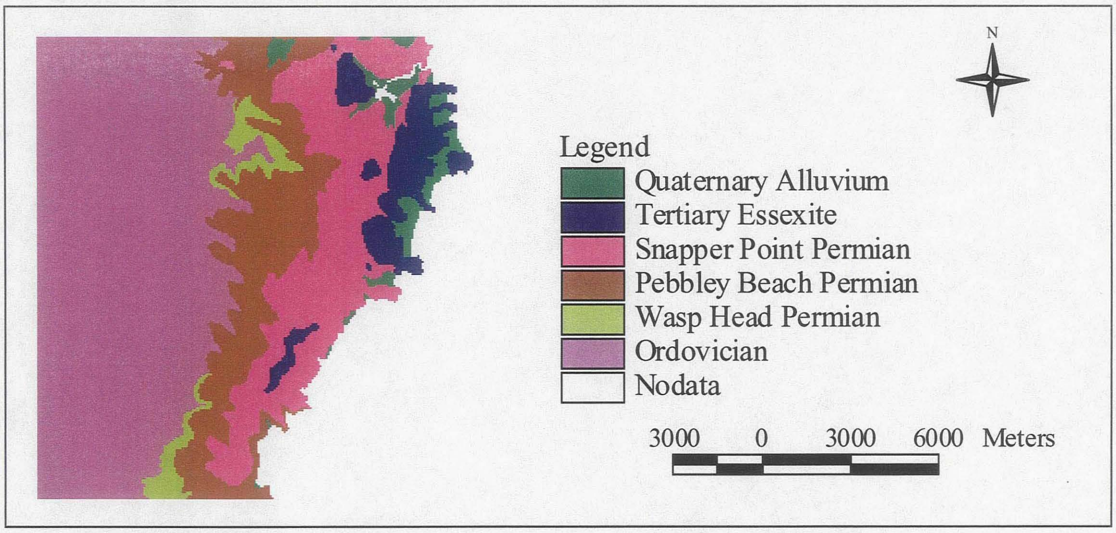


Figure 4.5 A geological dataset of the Kioloa Region

4.3.2.4 Roads and tracks dataset

The road and tracks in the Kioloa Region have been digitised and were saved in separate vector files in ArcInfo®. The road vector file comprises bitumen roads including the Princes Highway (A1) passing through from north to south and Murramarang Road along the coast. These roads are permanent infrastructure in the region and therefore will not be subjected to any new land use allocation. The tracks include access roads to forests and also many gravel roads in the region.

4.3.2.5 Park boundaries

The parks boundary dataset was obtained from New South Wales National Parks and Wildlife Services (NSWNPWS, 2004). The dataset includes boundaries for all the National Parks, Nature Reserves, Regional Parks, State Conservation Areas, Aboriginal Areas and Historic Sites under the jurisdiction and management of NSW NPWS. The parks boundaries within the Kioloa region were obtained from the whole dataset. The region contains seven parks which include two Nature Reserves, on Brush Island and Belowla Island. These islands are not taken into account in the MOLAA problem.

4.4 Summary

This chapter has discussed the research framework developed for accomplishing the stated objectives of this research. The framework includes eleven steps, beginning with the identification of stakeholders to incorporate the compactness function in the algorithm. These steps were discussed briefly in the context of a hypothetical MOLAA problem. The location, physical setting and available digital datasets of the study site were also discussed. Each step of the framework will be discussed in Chapter 5.

Chapter 5

METHODOLOGY

5.1 Introduction

This chapter describes the design of a hypothetical MOLAA problem, the preparation of land use suitability models and the input datasets appropriate to the methods. Finally, it describes the implementation of each method in solving a MOLAA problem.

5.2 Designing a hypothetical MOLAA problem for the Kioloa Region

5.2.1 Land use issues and objectives

The Kioloa region contains two national parks (Murramarang and Meroo), two nature reserves (Belowla and Brush islands) and the Murramarang Aboriginal area with high conservation values for native flora and fauna. Along the coast, there are motels and shopping areas providing services to increasing numbers of holidaymakers. A forestry operation is still active in the area and provides employment opportunities for local people. Agriculture and farming activities are also important for producing various agricultural products and livestock for supporting the local economy. From the land use perspective, the region is being used to meet the following objectives:

- Conservation of native flora and fauna;
- Conservation of soil and water quality and quantity;
- Timber supply;
- Development of eco-tourism and water recreation facilities;
- Sustainable production of agriculture and livestock;
- Developing areas for motels and other residential facilities.

These objectives encompass social, economic and environmental issues within land use planning in the Kioloa region. However, some economic and conservation goals are incompatible. For instance, maximizing the economic benefits from timber harvesting and the conservation of native flora and fauna in the same land unit is impossible.

Hence, the attainment of an economic goal often necessitates the sacrifice of a conservation goal and vice versa (van Lier, 1998). The growing influx of holidaymakers and visitors to the region is offering the prospect of economic gain, but is demanding more land from conservation, agriculture and forestry land use for the construction of motels and other facilities. Although agricultural and forestry activities may have lower economic returns per unit area than the tourism business, they have their own importance from a production point of view. If conservation areas are used for development purposes, the aesthetic and natural beauty of the region may be degraded and it might not be as attractive a destination for visitors. Reconciliation of these conflicting land use objectives and the provision of a best combination of land uses to ensure natural integrity and sustainable development are the major challenges to be tackled by land use decision-making.

The land use objectives discussed above can be met by dividing the region into four broad land use categories: conservation, agriculture, forestry and development. Some of the objectives may fall into more than one land use. To achieve the final land use allocation, the planner/decision maker should decide on what area is to be allocated to each land use type and which parameters, decision variables or criteria should determine the land use allocation decision. It is obvious that these land uses are a prerequisite for achieving the objectives stated above. If any of the land uses ceases to exist, the associated objectives cannot be met. In real land use planning, stakeholders and planners need to agree on the area required for each land use type. In this hypothetical problem, the land use types were prioritized in the following order: conservation, agriculture, forestry and development in order to meet the above objectives. The area requirements for these land uses were chosen to be 50, 25, 15 and 10 percent of the region, respectively, excluding roads, stream networks and the ocean. This represents a fundamental decision for land use planning and the final outcome will result in allocating that percentage of the land area to the respective land use category.

A decision framework for the hypothetical MOLAA problem is presented in Figure 5.1. This framework establishes the objectives for each land use, some strategies for achieving each objective, and the criteria to be applied to each strategy. The criteria are determined for each social, economic and environmental parameter on the basis of a review of the literature, expert consultation and personal experience. These criteria form the basis of the land use decision-making process and allow the decision-maker to incorporate the interests, values and preferences of all the stakeholders to try to achieve a consensus on the proposed land use.

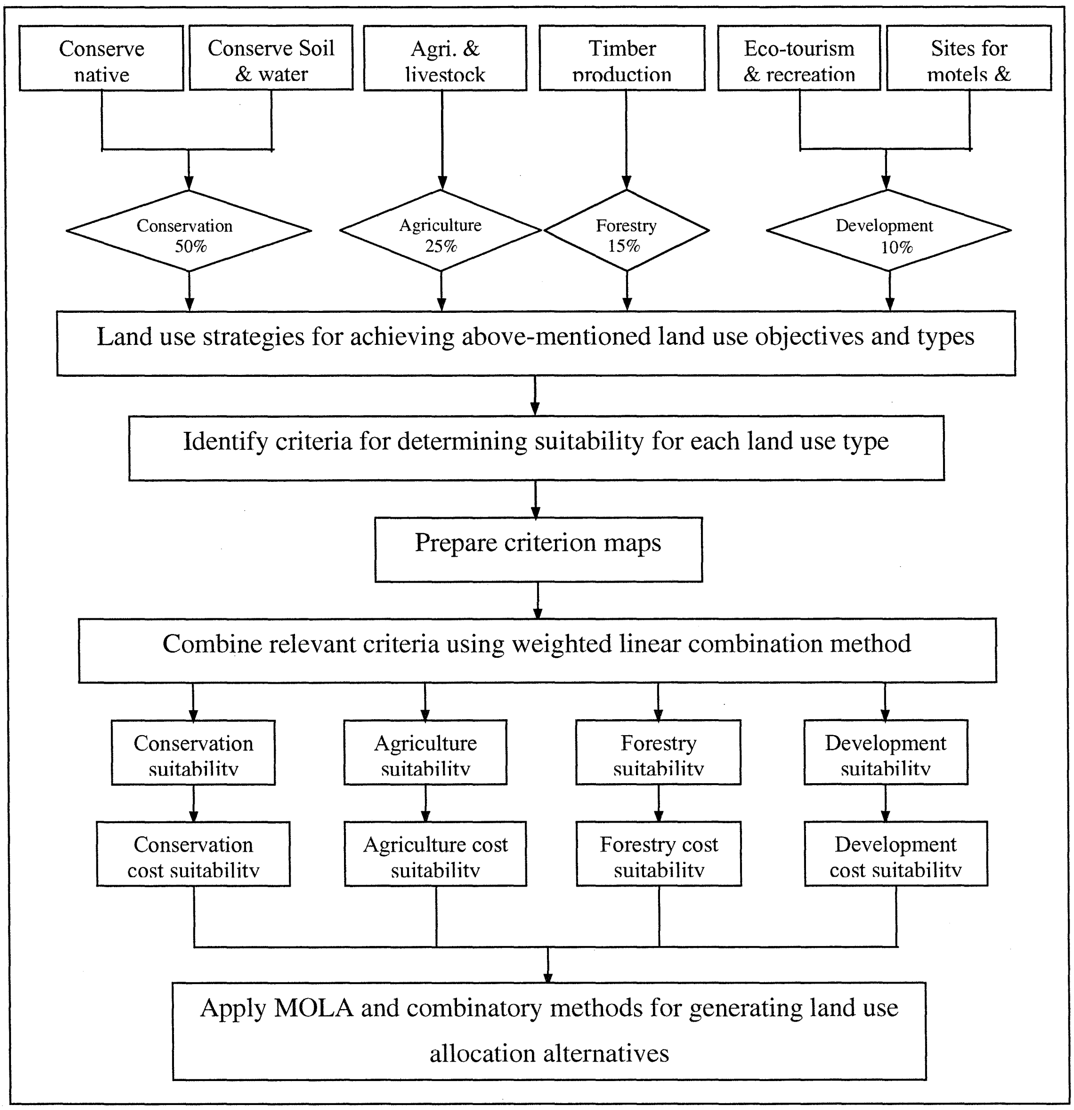


Figure 5.1 Decision framework for a hypothetical MOLAA

5.2.2 Determining criteria for land use types

The criteria stated in the decision framework were translated into suitability maps for assessing the relative suitability of each land unit for the desired land use types. For this hypothetical example, altogether 17 criteria including 16 factors and one constraint were used. The criteria used for each land use are discussed in the following section. The thresholds for the best suitability and least suitability for these criteria, based on the literature and expert knowledge for different land uses, are given in Table 5.1.

Table 5.1 Thresholds for criteria used for different land use types

Land Use	Criteria															
	Wildness/Access (m)		Wetland Buffer (m)		Vegetation/land Cover (type)		Slope (degree)		Elevation Value (m)		View Value (degree)		Beach Value (m)		Geology (type)	
	Best Suitable	Least Suitable	Best Suitable	Least Suitable	Best Suitable	Least Suitable	Best Suitable	Least Suitable	Best Suitable	Least Suitable	Best Suitable	Least Suitable	Best Suitable	Least Suitable	Best Suitable	Least Suitable
Conservation	> 3000	< 1000	< 150	> 600	RF, RFE, HL	OL,	> 25	< 10	-	-	-	-	-	-	-	-
Relative weight	0.12		0.16		0.48		0.24									
Agriculture	-	-	-	-	OL	RF, RFE, HL	< 5	> 15	-	-	-	-	-	-	O	QA, TE
Relative weight					0.1		0.45								0.45	
Forestry	< 500	> 3500	> 600	< 300	RF, RFE		< 5	> 15	-	-	-	-	-	-	-	-
Relative weight	0.13		0.08		0.395		0.395									
Development	< 200	> 1500	-	-	-	-	< 5	> 20	> 200	< 50	45 - 135	> 270 - < 45	<500	> 3000	-	-
Relative weight	0.09						0.11		0.14		0.22		0.44			

Notes: RF = Rain Forest; RFE = Rain Forest Ecotone; HL = Heath Land; OL = Open Land; DS = Dry Sclerophyll; WS= Wet Sclerophyll; O = Ordovician, WHP = Wasp Head Permian; PBP = Pebbly Beach Permian; PP = Snapper Point Permian; TE = Tertiary Essexite; QA = Quaternary Alluvium

5.2.2.1 Conservation land use

The primary objective of conservation land use is to allocate areas of high importance from a natural perspective in order to protect rainforest, wetlands and wilderness. Four criteria maps, namely land cover type, wilderness, wetland buffer and slope were used to assign suitability for conservation land use (See Table 5.1). In the land cover map, the Rainforest (RF), Rainforest Ecotone (RFE) and Heath Land (HL) are given the highest conservation values. Inaccessible areas (> 3000 metre from the road) are given higher wilderness value than the accessible areas (< 1000 metre from the road) from a conservation viewpoint. The 150 metre buffer areas on either side of the stream networks are considered high value for conservation of wetland areas, whereas areas beyond 600 m are not considered important at all. Areas with slopes above 25 degrees might be prone to heavy soil erosion if subjected to any other land use, therefore such areas are also worth conserving. Slopes of less than 10 degrees are not considered important for conservation for preventing soil erosion. The creation of criteria maps will be discussed in section 5.3.

5.2.2.2 Agriculture land use

The suitability of an area of land for agricultural use may be assessed by using limiting factors like soil fertility, irrigation facility, erosion, soil tillage and distance to markets (Nehme and Simões, 1999). In this hypothetical problem, the available datasets were geology, slope and land cover type for assessing land suitability for agricultural use in the Kioloa region. Geology type was assigned as indicator of soil fertility for agricultural production. The slope factor was used to confine the agricultural activity to flat land. In the geological dataset, Quaternary Alluvium (QA) and Tertiary Essexite (TE) were considered the most suitable and Ordovician (O), the least suitable for agricultural land use. Areas with less than 5 degree slope were considered the best and those with greater than 15 degree slope were deemed unsuitable for agricultural use. Open land cover type was judged to be the most suitable and the areas of the highest conservation values (Rainforest/Rainforest Ecotone/Heath Land) were deemed the least suitable areas for agriculture (See Table 5.1).

5.2.2.3 Forestry land use

The suitability of a land unit for forestry use was assessed by using four criteria maps: forest value, slope, accessibility and wetland buffer (See Table 5.1). The potential timber value of the vegetation types was used to quantify their values for the forestry land use. In the Kioloa region, the timber from the Rain Forest, Rain Forest Ecotone and Low Wet forest tree species had a high market value. The land under these species was thus regarded as the best for forestry land use and Dry Schlerophyll, Wet Schlerophyll, Heath and Open land were the least valuable for forestry land use. Land with a slope below five degrees was considered the best and slope above 15 degrees was considered as the least suitable for forestry. Easily accessible land, that is, less than 500 metres from the existing road network, was considered the most suitable and more than 3,500 metres away from the road was the least suitable for forestry land use, from an accessibility viewpoint. Areas adjacent to streams (less than 300 metres on either side) were considered the least suitable and 600 metres away from streams were considered the best land for forestry purposes.

5.2.2.4 Development areas

For the development area, distance from the beach, value of the view, elevation value, slope and access were used as the criteria for evaluation (See Table 5.1). Land at a distance of 500 metres from the beach was seen as the most suitable land and land that was more than 3,000 metres away from the beach was considered the least suitable land for residential purposes. Regarding view value, the southeast aspect (45 degrees to 135 degrees) was given the highest suitability and northeast or northwest (less than 45 degrees and greater than 315 degrees) views were the least preferred for development land use. A low slope (below 5 degree) and high elevation (above 200 metres) were considered the best and steeply sloping land (above 20 degree) with low elevation area (below 50 metre) were the least preferred land for development land use. Less than 200 metres distance to the road network was considered the most suitable and higher than 1500 metres was taken as the least suitable land for development land use. Besides these factors, flooding due to storm surge and elevation was considered as a constraint to development land use. This constraint model was incorporated into the final cost model for development land use.

5.3 Land suitability assessment approach

The datasets available for the Kioloa region are a Landsat TM 7, a digital terrain model (DTM), geology and road vectors available at the Australian National University. A vegetation cover or land cover map with 10 classes was derived from unsupervised classification and field check of the Landsat TM image using green, near infrared and mid infrared bands. The DTM was used to generate a stream network, slope, elevation and aspect model using the terrain modelling routines in the Arc Info® GIS.

The input database of spatial data layers X comprises i rows and j columns and each cell can be represented by x_{ij}.

$$X = \{ x_{11},\ x_{12,\ldots\ldots\ldots\ldots}\ x_{IJ} \} \qquad \text{Equation 5.1}$$

Where Row i = 1,……..,I ; column, j = 1,……..,J.

The set of land use types is represented by K having a set of criteria L. For x_{ij} land unit with land use k, the value of criterion l is given as follows:

$$x_{ijkl} = \{ x_{ijk1},\ x_{ijk2,\ldots\ldots\ldots\ldots}\ x_{IJKL} \} \qquad \text{Equation 5.2}$$

Where land use type k = 1,2……...K ; criteria l = 1,2………L

Two different techniques were used to create land use suitability models and were subsequently used as inputs for land use allocation by the combinatorial and MOLA module in IDRISI®.

5.3.1 Land use suitability models using ordinal - WLC

In ordinal-WLC, a land use suitability model was created for each land use by combining the ordinal scale criteria maps based on their relative weights. This method applies equation 2.6 given in Chapter 2 for deriving a land use suitability value for each land unit, using the thresholds for best suitability and least suitability for these criteria (Table 5.1). The thresholds for the most and the least suitable attributes were assigned two extreme values, 5 and 1, in the ordinal scale respectively. The intermediate values 4, 3, and 2 were used to signify suitable, fairly suitable and less suitable attribute classes of a criterion. However, the road network and stream network (excluding stream order 1 and 2) were taken as mandatory land uses and not considered for suitability mapping for the proposed land uses. The ordinal classification of each criterion was accomplished in ArcInfo® GIS software. The criteria, relative weights and attribute classification in the ordinal scale (1 - 5) are given for conservation, agriculture, forestry and residential land uses in Tables 5.2, 5.3, 5.4 and 5.5, respectively.

Table 5.2 Criteria and attribute classification in ordinal scale for conservation

Criteria	Relative weight	Attribute classes 1	2	3	4	5
Slope (degree)	0.24	< 10.0	10.0 - 15.0	15.0 - 20.0	20.0 - 25.0	> 25.0
Vegetation (type)	0.48	OL	DS,DM	WS,WM	-	RF, REF, H
Wetland (m)	0.16	600 – 9000	-	300 - 600	150 - 300	< 150
Wildness (m)	0.12	< 1000	1000 - 1500	1500 - 2000	2000 - 3000	3000 – 9000

Table 5.3 Criteria and attribute classification in ordinal scale for agriculture

Criteria	Relative weight	Attribute classes 1	2	3	4	5
Slope (degree)	0.45	> 15.0	10.0 - 15.0	-	5.0 -10.0	< 5.0
Geology (type)	0.45	O	WHP	PBP	SPP	QA, TE
Land cover (type)	0.10	RF, REF, H	-	DS, DM	WS, WM	OL

Table 5.4 Criteria and attribute classification in ordinal scale for forestry

Criteria	Relative weight	Attribute classes 1	2	3	4	5
Slope (degree)	0.395	> 15.0	-	10.0 - 15.0	5.0 - 10.0	< 5.0
Accessibility (m)	0.13	3500 – 9000	2500 - 3500	1500 - 2500	500 - 1500	< 500
Stream buffer (m)	0.08	< 300	300 - 600	-	-	600 – 9000
Forest value (type)	0.395	WS, WM, H, OL	DS, DM	LW	-	RF, REF

Table 5.5 Criteria and attribute classification in ordinal scale for development use

Criteria	Relative Weight	Attribute classes 1	2	3	4	5
Beach distance (m)	0.44	3000-9000	2000-3000	1000-2000	500-1000	< 500
Elevation (m)	0.14	< 50	50-100	100-150	150-200	200-300
Accessibility (m)	0.09	1500-9000	700-1500	400-700	200-400	< 200
Slope (degree)	0.11	> 25.0	15.0-20.0	10.0-15.0	5.0-10.0	< 5.0
View value (degree)	0.22	0-45, 270-360	225-270	180-225	135-180	45-135
Flood constraint	-	No flood	-	-	-	Flood risk

After creating the basic input datasets and estimating the relative weight of each factor by using the pair-wise comparison method, the grids were combined using the WLC method to generate a land use suitability map for each land use category. Values ranged from 1.0 to 5.00 in land use suitability layers, representing the lowest and the highest suitability, respectively (Table 5.3). These land use suitability models were created by applying ordinal-weighted linear combination (WLC) and the suitability models are called ordinal land use suitability models or ordinal models. In contrast to the MCE module in IDRISI®, the constraint layer, that is, the flood constraint map, is incorporated during the preparation of the cost suitability module for the combinatorial methods. The procedure will be described in section 5.4.2.

5.3.2 Land use suitability models using continuous – WLC

In this land use suitability model, factors like slope, elevation, distance from the road or stream network, were used in a continuous scale. In these data sets, the higher/lower value represents either the most or the least suitable area for a particular land use. For example, the suitability for agricultural land use will increase with lower slope value and the land unit becomes less suitable for agricultural use as the slope value increases. The models were generated in IDRISI® software and the procedure is described in the following paragraphs.

First, the datasets in ArcInfo® grid format were imported into the IDRISI® software. As the factor maps have different ranges of values representing relative suitability for land use, these maps need to be standardized in order to transform all the values into an identical scale. Standardization of all the factor maps to a 0-255 byte binary range by a simple linear stretch was carried out using STRETCH menu in IDRISI® software. However, in the case of factor maps like slope for agriculture, distance from beach for development land use, the lower value is more suitable for these land uses but STRETCH assigned the lowest attribute value to zero in 0-255 scale. Hence, the values in such factor maps were inverted by running INITIAL and OVERLAY in order to assign the lowest attribute value to the highest value (255) in the scale and vice versa. The same relative weights were used to combine relevant factor maps for each land use using MCE module in IDRISI® software. A Boolean constraint map was also incorporated in this module to exclude mandatory land uses from suitability consideration. The outputs from this operation generated a land use suitability model for each land use type. In the case of development land use, the flood constraint map was incorporated in the MCE module to create a suitability model for applying the MOLA module. In the case of combinatory methods, the flood map was used as a cost model and applied during the creation of the cost model. The relative suitability values for cells in the large grid, *S* ranged from 38 to 255, representing the least and the best suitability for the land use. These land use suitability maps generated from the factor maps in a continuous scale, except for the land cover type and geology, are denoted as continuous-land use suitability models or continuous models. The land use suitability models in continuous scale were finally exported to ArcInfo® software to create input models (cost models) for the combinatory methods. The procedure will be described in section 5.4.2.

5.3.3 Land use suitability using fuzzy - WLC

In this method, the attribute classes of each criterion were classified in a fuzzy scale. As this scale ranges between 1 and 0, the best attribute class with respect to a land use is assigned to 1 and less suitable classes are assigned a value less than 1, based on relative suitability. The lower the suitability of an attribute class, the closer a value to 0 is assigned. Fuzzy classification of criteria was accomplished by using the appropriate model based on Equation 2. 10 as explained by Kollias and Kalivas (1998) (discussed in Chapter 2).

In order to apply the model given by Equation 2.10 (in Chapter 2) to different criteria maps, three modifications of the above model were derived to suit the relative importance of attribute classes to land use type.

Left hand asymmetric: This model assigns membership function 1 to above or equal to central value (b_1). For example, classification of slope for conservation, slope equal or greater than 25 degree is assigned 1 (Equation 5.3).

$$MF(x_i) = 1 \qquad \text{for } x_i >= b_1 \qquad \text{Equation 5.3}$$

Right hand asymmetric: This model assigns membership function 1 to equal or less than the central value (b_1) (Equation 5.4). For example, classification of distance from beach for development land use, 500 metre or less distance from beach is assigned 1. This function applies opposite logic to Equation 5.3.

$$MF(x_i) = 1 \qquad \text{for } x_i <= b_1 \qquad \text{Equation 5.4}$$

Optimum range: This model assigns membership function 1 to a range of attribute values between b_1 and b_2. In the case of view value for development land use, an aspect with between 45 degrees and 135 degrees is to be assigned 1. In this model, b_1 and b_2 may use the same (d) or different values (d_1 and d_2) (Equation 5.5).

$$MF(x_i) = 1 \qquad \text{for } b_1 <= x_i <= b_2 \qquad \text{Equation 5.5}$$

The same criteria used for ordinal or continuous land use suitability models were classified using fuzzy sets for deriving a land use suitability model. The appropriate fuzzy model and the parameters (*b* and *d*) were defined for each criterion. Table 5.6 provides information about the criterion used, its data type (continuous or ordinal), selected model and parameter values.

Table 5.6 Criteria, their data types, range of values and fuzzy model applied with parameter values for different land use types

SN	Land use and Criterion	Data type	Range of values	Model applied	Parameter values			
					b_1	b_2	d_1	d_2
1	Conservation							
1a	Slope (degree)	C	0.00 – 36.72	1	>=25	-	5	-
1b	Vegetation (type)	O	1 – 5	1	>=5	-	2	-
1c	Wetland (metre)	C	0.00 – 7980.00	2	<=150	-	150	-
1d	Wildness (metre)	C	0.00 – 8431.00	1	>=3000	-	1000	-
2	Agriculture							
2a	Geology (type)	O	1 – 5	1	>=5	-	1	-
2b	Slope (degree)	C	0.00 – 36.72	2	<=5	-	5	-
2c	Land cover (type)	O	1- 5	1	>=5	-	1	-
3	Forestry							
3a	Accessibility (metre)	C	0.00 – 8431.00	2	<= 500	-	1000	-
3b	Slope (degree)	C	0.00 – 36.72	2	<=5	-	5	-
3c	Stream buffer (metre)	C	0.00 – 7980.00	1	>=600	-	300	-
3d	Forest value (type)	O	1 - 5	1	>=5	-	1	-
4	Development							
4a	Beach distance (metre)	C	0.00 – 11621.31	2	<=500	-	500	-
4b	Elevation (metre)	C	0.00 – 279.00	1	>=200	-	50	-
4c	Accessibility (metre)	C	0.00 – 8431.00	2	<=200	-	200	-
4d	Slope (degree)	C	0.00 – 36.72	2	<=5	-	5	-
4e	View value (degree)	C	-1.00 – 359.421	3	>=45, <=135	<45, >135	10	10

The fuzzy classification of each criterion was accomplished by writing an AML (Arc Macro Language) and running it in the Grid of ArcInfo®. The criteria maps for each land use types were combined by applying the same weighting to each criterion as in ordinal and continuous methods. The Boolean map of mandatory land use was also incorporated into the land use suitability models for all the land uses to exclude these areas from allocation. The relative suitability values ranged between 0.00001 and 0.62576 in the land use suitability maps generated by the fuzzy method.

5.4 Land use input models for different methods

5.4.1 For MOLA

5.4.1.1 Ordinal land use suitability model

To apply the MOLA module to the hypothetical MOLAA problem, a land use suitability model for each land use was created in an ordinal scale using MCE module in

IDRISI® software. All the criteria maps in ordinal scale were imported into the IDRISI® software from ArcInfo® software. The data in these files were stretched on a 0 – 255 scale using CONVERT module. All the cells with value 1 in ArcInfo® grid were changed to 51 and the cell value 5 was changed to 255 in the stretched files. NODATA and flood constraint grids were also imported in Idrisi raster format as Boolean maps and converted into byte binary format. The MCE module combined all the factor maps by using the Weighted Linear Combination method and produced a land use suitability map for each land use as output. In the case of the development land use, the Boolean constraint map for flood prone areas was also incorporated in the MCE module. All the cells in the constraint maps (mandatory land use and flood prone areas) were assigned 0 in these land use suitability models. A small grid of 10 by 10 cells was cut from the large grid to analyse the land allocation by MOLA.

The MOLA module in IDRISI® uses cell value in the input model for allocating land use that meets the specified area requirement for each land use type. To facilitate the comparison of the cell values in different input models, ranking of all the cells in the MCE suitability model was accomplished using RANK module, in ascending order according to their cell value. In the rank output files, the cell with the highest value in the suitability module was assigned 1, the second highest value 2 and so on. The cells in the constraint areas with 0 value in the suitability modules were also ranked. Those cells with the same value were ranked, randomly assigning a unique value to each cell. These rank files were used as inputs to the MOLA module. The land use suitability models in the small grid were also ranked using the same module.

5.4.1.2. Continuous land use suitability model

The same procedure as described in Section 5.4.1.1 for the ordinal land use suitability model was used to create rank maps of the continuous land use suitability model.

5.4.2 For Combinatorial methods

Combinatory methods yield an optimum combination of multiple land uses through the process of minimization of the cost function. To be able to employ the land use suitability model in terms of land use cost, the suitability models were converted into cost suitability models (*CSM*) or cost model using Equation 5.6.

$$CSM = \left[\left(\frac{1}{suitability\ model} \right) \times constraint\ cost\ model \right] x \text{ Factor} \quad \text{Equation 5.6}$$

In this equation, the suitability maps are inverted in order to change the highest suitability value to the lowest cost value and the lowest suitability value to the highest cost value. For example, the highest suitability value (5.0) in the ordinal model was transformed to the lowest cost value (0.2) and the lowest suitable value (1.0) to the highest cost value (1.0). However, these suitability models were based on factors only (see sections 5.3.1). If there are constraints on any land use alternative, they need to be incorporated in the cost models. In multi-criteria evaluation, a constraint imposes a restriction on a specific land use and the areas under constraint are excluded using Boolean logic, assigning zero to the area under constraint and one to the rest of the area, as discussed earlier in section 5.4.1.1 (Eastman *et al.*, 1993). The application of this logic to any land use cost model will reduce the area under land use consideration. To maintain the integrity of the input datasets, the areas under constraint should also remain in the decision space. An area under constraint may also offer suitability for a particular land use due to exhibiting several suitability factors but comparatively less suitability than the area without constraint.

In some circumstances, a constraint area may be used for a land use by remedying its potential effect. For example, flooding may be a constraint for a residential area. Nevertheless, a flood-prone area may still be used for residential purpose, if some protective measures and an insurance policy (for loss of property from flood hazard) are considered. However, in terms of cost, areas under constraint may be more expensive to use than areas without constraint. This logic may be applied to create a cost suitability model by incorporating the constraint model as given by Equation 5.6. A constraint model should be prepared by assigning higher values (greater than 1) to the constraint area and 1 to the non-constraint areas.

In this problem, flooding was considered as a constraint to development land use. A flood constraint model was developed and 5 was assigned to flood-prone areas and 1 to non flood-prone areas. When this flood constraint model was applied in Equation 5.6, the areas prone to flood hazards became five times costlier than the non-flood prone areas in the cost models, rendering these areas relatively more unsuitable for development purposes. The resultant cost values for development land use ranged between 0.223 and 3.785 in the ordinal model, 0.00417 and 0.10417 in the continuous model and 0.01129 and 0.62576 in the fuzzy model.

Finally, the reciprocal of the suitability model with or without a constraint model was converted into integer values by multiplying the ordinal cost model by a factor of 1000, and the continuous and fuzzy cost models were multiplied by a factor of 10,000 as shown in Equation 5.6. The cost model for each land use type provides a discrete cost value for each land unit and offers a numeric comparison of the relative suitability between the land use types to a land unit. The land use with the lowest cost value is the most suitable land use for the land unit. The small grid (10 by 10 cells) and the medium grid (100 by 100 cells) were cut out from large cost models (525 by 525) to assess the performance of simulated annealing for solving different grid size MOLAA problems. The range of cost values, their means and number of discrete values for small, medium and large grid sizes of the ordinal, continuous and fuzzy cost models are given in Tables 5.7, 5.8, and 5.9, respectively. The ordinal, continuous and fuzzy cost suitability models are displayed in Figures 5.2, 5.3 and 5.4, respectively. The more costly land units are represented by the darker shading.

Table 5.7 Cost suitability values for small grid (10 by 10 cells) for all three cost models

Land use Type	Ordinal model			Continuous model			Fuzzy model		
	min	max	No of values	Min	max	No of values	min	max	No of values
Conservation	294	694	14	588	1428	35	1583	4686	100
Agriculture	322	606	6	666	854	28	1899	4667	55
Forestry	215	388	9	442	763	38	1073	2989	91
Development	436	3285	8	618	3268	28	2863	14330	92

Table 5.8 Cost suitability values for medium grid (100 by 100 cells) for all three cost models

Land use Type	Ordinal model			Continuous model			Fuzzy model		
	min	max	No of values	Min	max	No of values	min	max	No of values
Conservation	271	1000	37	546	1724	104	1469	8294	4169
Agriculture	281	833	13	552	1020	83	1834	9233	529
Forestry	200	506	38	425	900	100	1000	4354	1310
Development	308	3785	109	486	4311	177	2203	40405	5243

Table 5.9 Cost suitability values for large grid (525 by 525 cells) for all three cost models

Land use type	Ordinal model			Continuous model			Fuzzy model		
	min	max	No of values	Min	max	No of values	min	max	No of values
Conservation	223	1000	78	462	1960	166	1170	8472	7237
Agriculture	200	1000	36	392	1428	185	1000	15270	5761
Forestry	200	757	110	414	1515	174	1000	7550	4890
Development	223	3785	350	417	10417	363	1129	62576	17468

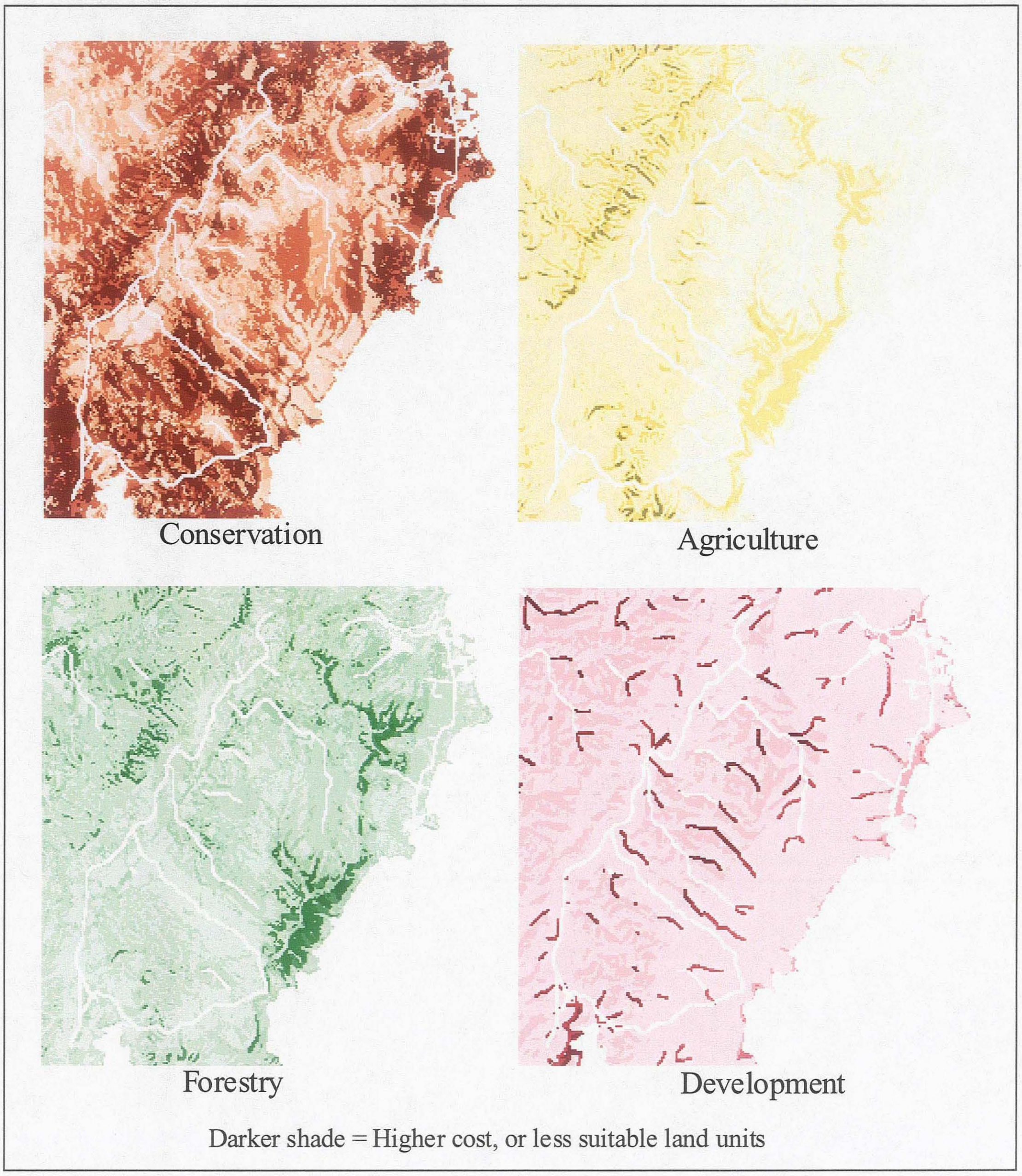


Figure 5.2 Ordinal cost suitability models for different land uses

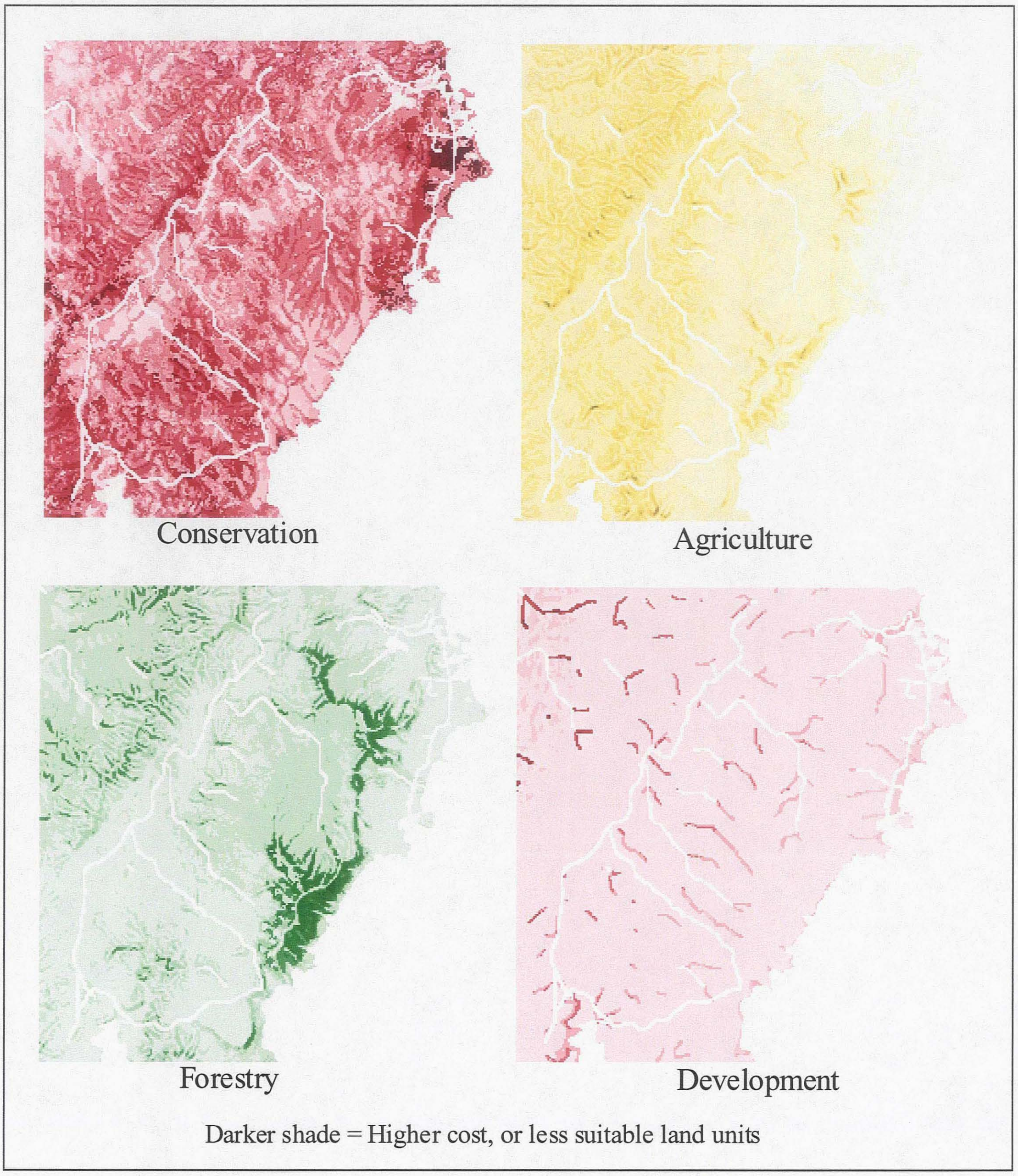


Figure 5.3 Continuous cost suitability models for different land uses

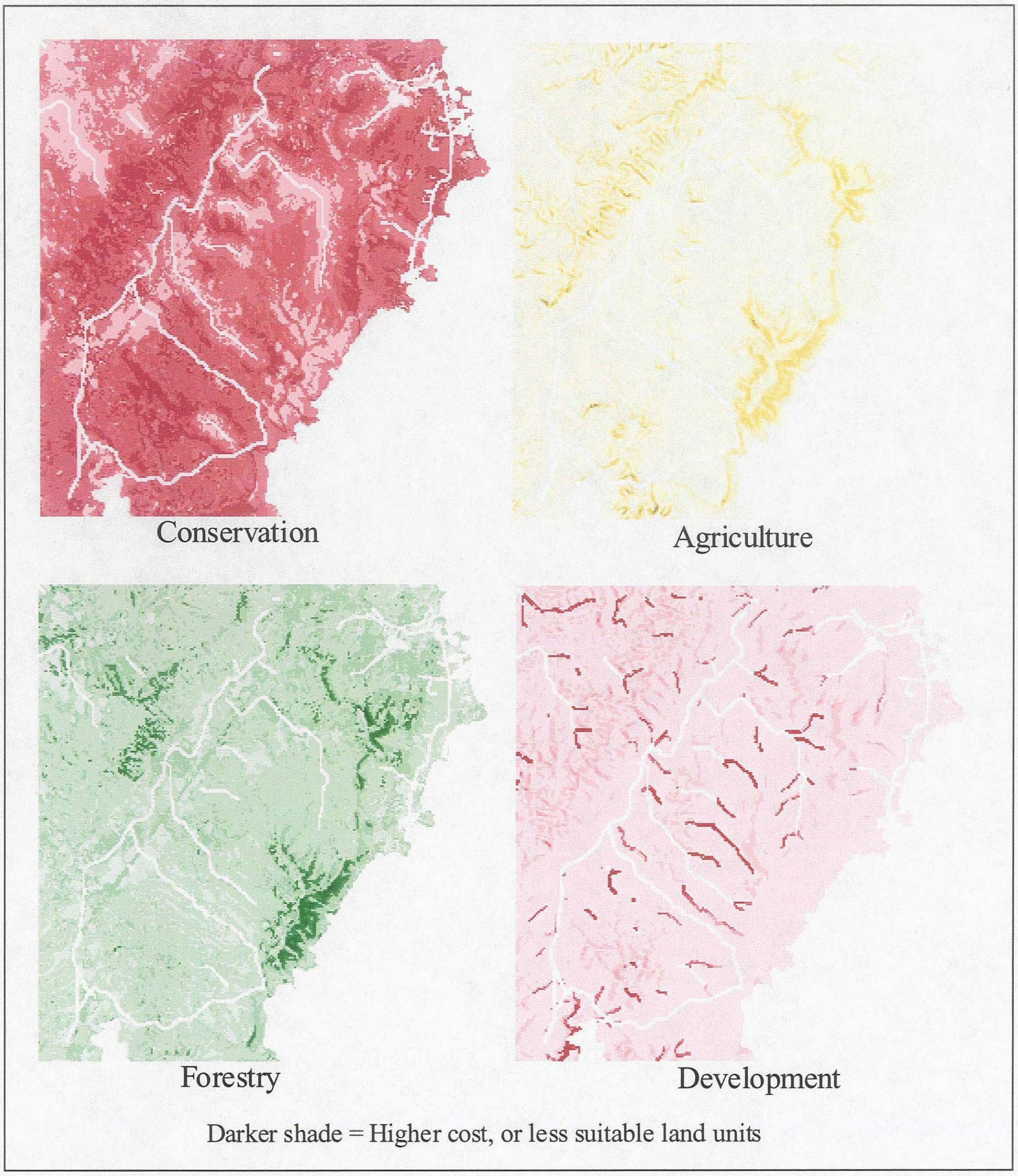


Figure 5.4 Fuzzy cost suitability models for different land uses

5.5 Applying MOLA Module and Combinatory methods to the hypothetical MOLAA problem

5.5.1 MOLA module in IDRISI®

Implementing a MOLA module in IDRISI® follows the same procedure as explained in section 3.3 in Chapter 3. Four land uses, their rank maps and area requirements were specified in the input window of the MOLA module. Equal weights were assigned for all the rank maps and no secondary image was used for prioritising the rank maps. The MOLA module produced the final land use allocation by allocating the same number of cells to each land use as specified in the input window. The solutions and the performance of this method will be discussed in Chapter 6.

5.5.2 Applying Combinatorial methods

5.5.2.1 Initial input solution for Combinatorial methods

Combinatorial methods generate a near-optimal solution from an initial solution by iterating several times unless the algorithm is terminated by the prescribed stopping rules. The initial solution provides a platform for combinatorial methods to reach the ultimate solution. The procedure for generating the initial solution may vary from problem to problem and may also influence the efficiency of the combinatorial methods. Aerts (2002) used a random input model as an initial solution for the land use allocation problem. In addition to this, I have used two other input models as initial solutions for implementing combinatorial methods and compared the results. The initial input generation techniques are described in the following section.

1. Random input model

The random input model was produced by executing a program '*rangrid.exe*' written in the C++ programming language by Leahy (2003a). This program uses a control file in *.txt* file format which specifies the number of cost models, area requirement in number of cells for each land use type and the name of the output file. The land use types indicated in the control file are merged using the cost models satisfying the area requirement for each land use. In order to merge all the land use types, this program randomly selected the prescribed number of cells for each land use from the respective cost model. The area requirements for the land uses were met sequentially, in the order stated in the control file. In this example, first the 93,059 cells were randomly selected from conservation cost model and allocated to conservation land use. Second, when the area requirement for conservation land use was satisfied, 46,530 cells were randomly chosen out of unassigned cells from the agricultural cost model for agricultural land use. Third, 27,918 cells were randomly selected from the remaining cells for forestry land use by using the forestry cost model. After satisfying the area requirements of three out of four land uses, the number of unassigned cells would be the same as the area requirement for the fourth land use. Here, the cells remaining after random allocation to conservation, agriculture and forestry land uses were assigned to development land use. These all cells had the same random chance to be allocated to one of the land uses.

This program finally produced a land use allocation model and a corresponding cost model in binary raster format with *.flt* file extension. These two models were imported in the Arc View® 3.2 GIS software and displayed in grid format.

2. Cheapest input model

The cheapest input model is the cheapest combination of all land uses based on the values in the cost model which also satisfies the desired area allocation for each land uses. It uses a two-pass process to generate the output grid. In the first pass, a linked list of records is created for each cell, containing the cell location and a value calculated from the input grids. The cost values for each land use are compared for each cell in the cost models and recorded in ascending order from the lowest to the highest cost value. In the second pass, land use with the cheapest cost value is assigned to each cell. If the area requirement of the land use with the cheapest cost has been met, the cell is assigned to the land use with second cheapest cost and so on. Finally the cheapest input model is generated by assigning the best possible land use with the cheapest cost to each land unit, satisfying the area requirement for each land use type. The cheapest input models for all the grid sizes of continuous cost model are shown in Figure 5.5.

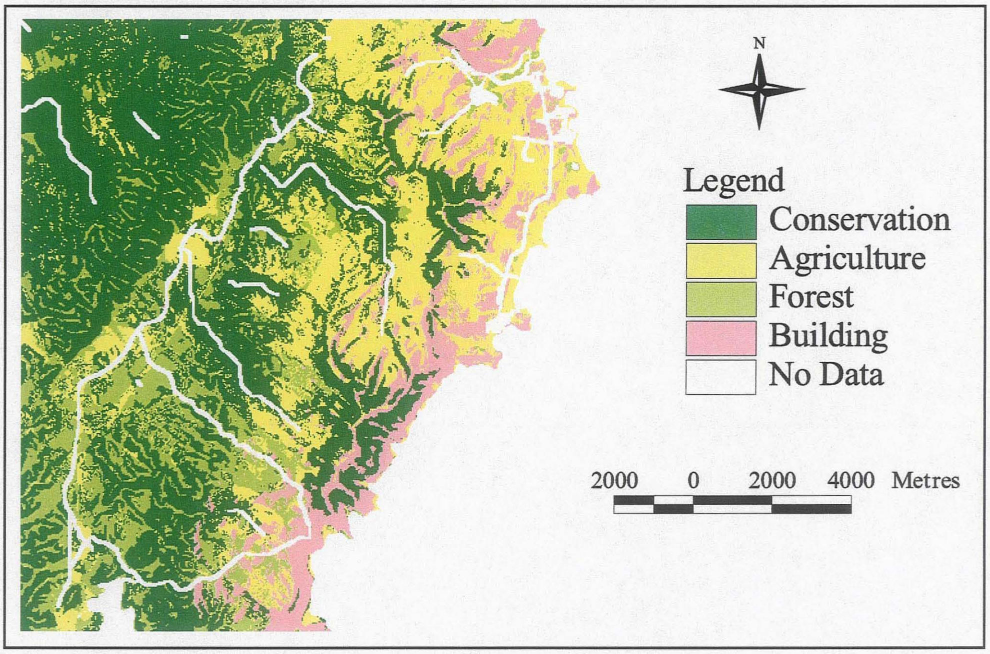


Figure 5.5 Cheapest initial input solution for the large grid of continuous cost model

3. Greatest difference input model

This model follows the same process as the cheapest input model. However, the linked list records the cell location with the difference value between the maximum and minimum cost values for that cell in the cost models. These values are recorded in descending order. In the second pass, land use with the greatest difference is assigned to a cell through assessing the linked list. If the area requirement of land use with the greatest difference has been met, the cell is assigned to the land use with the second greatest difference and so on. Finally the greatest difference input model is generated by assigning the best possible land use with the greatest difference to each land unit satisfying the area requirement for each land use type. It involves cost optimisation depending on the difference in the cost values for different land uses. If the cost difference is high in the input grids, this method produces a lower total cost than the cheapest cost method. The greatest difference input models for all the grid sizes of fuzzy cost model are shown in Figure 5.6.

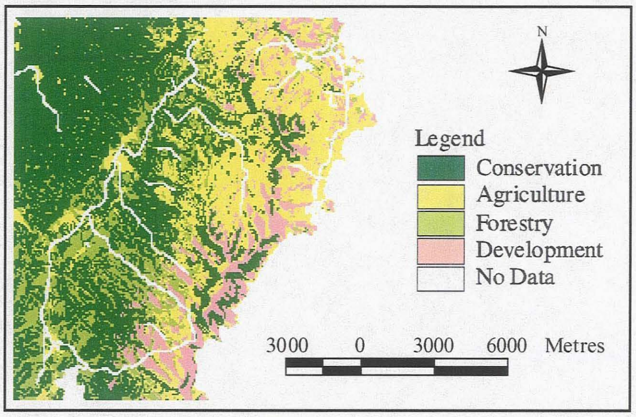


Figure 5.6 Greatest difference initial input solution for the large grid of fuzzy (cost suitability) model

A program '*mergrid.exe*' was written in C++ programming language by Leahy (2003b) for generating the cheapest input model and the greatest difference input model by selecting Mode 1 and Mode 2, respectively. To execute the program in both modes requires a control file specifying the number of input land use types, their area requirement and the name of the output file as given in Figure 5.6.

The total cost functions and mean cost values for three grid sizes are given for three different input models for ordinal, continuous and fuzzy cost models in Tables 5.10, 5.11 and 5.12 respectively. The run times for the large grid of the ordinal cost model were about 11, 16 and 18 minutes for merging four-land use cost models by random, cheapest and greatest difference method, respectively.

Table 5.10 Total and mean cost functions for different input solution and grid sizes for ordinal model

Grid Size	Random		Cheapest		Greatest Difference	
	Total cost	Mean cost	Total cost	Mean cost	Total cost	Mean cost
Small	47013	470.13	46654	466.54	45295	452.95
Medium	5291396	550.10	4986708	63.96	4561951	474.26
Large	93526457	502.51	84709562	455.13	76666864	411.93

Table 5.11 Total and mean cost functions for different input solution and grid sizes for continuous model

Grid Size	Random		Cheapest		Greatest Difference	
	Total cost	Mean cost	Total cost	Mean cost	Total cost	Mean cost
Small	89772	897.72	80969	809.69	80110	801.1
Medium	8967354	932.25	8610910	895.2	8174289	849.81
Large	166067628	892.27	164854381	885.75	160186567	860.67

Table 5.12 Total and mean cost functions for different input solution and grid sizes for fuzzy model

Grid Size	Random		Cheapest		Greatest Difference	
	Total cost	Mean cost	Total cost	Mean cost	Total cost	Mean cost
Small	309464	3094.64	314039	3140.39	263079	2630.79
Medium	40845342	4246.3	39855782	4143.4	36544927	37799.24
Large	710188157	3815.79	646727541	3474.8	586403903	3150.71

5.5.2.2 Applying Simulated Annealing

1. Determining the parameters for Simulated Annealing

For the MOLAA problem, Simulated Annealing aims to find a near optimum solution through minimization of the cost function. The search space and the cost function are the basic parameters to start the exploration of the optimum configuration of the land uses. However, the outcome of the algorithm is governed by cooling parameters like initial control parameter, rate of cooling, final values of control parameter, and the number of iterations per temperature step. Each of these parameters is discussed below in the context of the MOLAA problem.

I. Search space

The entire search space includes all the land units that need to be assigned to an optimum land use, and the number of land use alternatives. The land units with mandatory land use such as roads, streams or sea were excluded from the search space and treated as NODATA cells. In the search space, each land unit was defined by a double array cell x_{ij}. Because of the exclusion of the road and stream network and the ocean, the valid numbers of cells to be assigned with a land use were 100, 9619 and 186118 in the small, medium and the large grids, respectively.

II. Cost function (C_F)

The value of the cost function is the major criterion for assessing the performance of the algorithm. The initial cost function (F_i) was estimated by summing up the cost of all the valid pixels (Equation 3.10) with respect to their land use in the initial solution, as given by Aerts (2002).

The initial cost functions for different initial solutions for three grid sizes with three cost models are given in Tables 5.10, 5.11 and 5.12. This research applies the land use suitability model derived by using ordinal, continuous and fuzzy-WLC methods and subsequently transferring to cost models to apply combinatory methods. The cost was derived using several criteria relevant to each land use and combined by using relative weights. The procedures were discussed in Section 5.2.

III. Neighbourhood solution generation

The interchange or swap method was used for generating a new solution at each iteration. In order to accomplish a swap, two cells were randomly selected and land uses were exchanged between them. Where one or both of them were NODATA cells, land uses were not exchanged and a fresh random selection was carried out. Subsequently, a new cost function was calculated by using the cost grid for the new combination of land uses. Every exchange of land uses between two selected cells was counted as a swap or iteration. This process was repeated to generate a new neighbourhood solution until the defined number of swaps was achieved. In order to distinguish each swap based on its impact on the cost function, the swaps were counted as cold-swap or hot-swap depending upon whether the swapping resulted in minimization ($F_i > F_j$) or maximization ($F_i < F_j$) of the cost function, respectively. If there was no change in the cost function ($F_i = F_j$), the swapping of land use did not take place and was counted as no swap.

IV. Initial control parameter (T_1)

Aerts (2002) used an initial control parameter that accepted about 80 percent of the total increasing cost function for a land allocation problem, as suggested by van Laarhoven (1987). To find an appropriate control parameter for a MOLAA problem, an attempt was made to judge the effect of the initial control parameter on the optimisation by running the algorithm at low (L), medium (M) and high (H) values of the control parameter, as determined by the hot-swap acceptance of about 50, 80 and 98 percent, respectively.

V. Cooling function

The control parameter should be cooled down after attempting the prescribed number of swaps (*S*) at each control parameter step (*N*). In order to find an appropriate cooling function for the MOLAA problem, the following three cooling functions as given by Equations 3.6, 3.8 and 3.9 were tested for running Simulated Annealing and were denoted Mode 1, Mode 2 and Mode 3, respectively.

In Mode 1, the initial control parameter was cooled at four different cooling rates by using the value of R as 0.2, 0.5, 0.8 and 0.98 and were denoted as very fast (VF), fast (F), slow (S) and very slow (VS) cooling rates respectively. However, other two cooling functions (Equations 3.8 and 3.9) also required final control parameter (T_n) and the number of control parameter steps (N), besides the initial control parameter (T_1). These values were obtained by running the algorithm in Mode 1.

VI. Number of swaps per step (Sp)

The exchange of land uses between two randomly selected cells yields a new neighbourhood solution, thereby bringing about a small change in the land use pattern and the cost function. The number of iterations per step was assigned based on the multiple of neighbourhood size. The appropriate number of swaps for a MOLAA problem with different grid sizes was found by testing a range of valid neighbourhood sizes in the grid. The swapping rate as low as the number of valid cells in the grid and as high as 500 times the number of valid cells in the grid was tested to identify an appropriate number of swaps per step for a MOLAA problem.

Aerts (2002) used 100 and 1000 swaps per step for a grid of 10 by 10 cells and obtained the same cost function for both swapping rates. However, he did not mention the number of swaps used in the case study with an area of grid size 300 by 300 cells. Sundermann (1996) suggested using the number of iterations per step at which the cost function culminates. This requires several trials with different numbers of iterations. Another method for determining the number of iterations per step is based on the multiple of neighbourhood size (Pirlot 1996). Pirlot's method is found to be straight forward method for finding the number of iteration per stem and hence, applied in this research. The neighbourhood size for this problem was taken to be the number of total cells excluding the nodata cells in the grid. The appropriate number of swaps for a MOLAA problem with different grid sizes was found by testing a range of valid neighbourhood sizes in the grid.

VII. Stopping rule

The main aim of the algorithm is to generate a near-optimum solution by minimizing the cost function. As soon as this solution is reached, the algorithm has to be stopped. As long as there is a possibility of cold-swap ($F_i > F_j$), there is a chance of improving the cost function. At the stage when there is no more cold-swapping, the system ceases to produce any further improvement in the cost function and therefore yields the lowest cost function value for the run. This criterion was used as the stopping rule by assigning a condition at which the cold-swap became zero throughout the control parameter step, and the algorithm was terminated. This rule was specifically applicable to the cooling function (Equation 3.6) where the final control parameter was set to zero and the algorithm can proceed indefinitely by reducing the initial control parameter at the rate of the R factor to zero. However, for other cooling functions in Mode 2 and Mode 3, the number of steps (N) and the final control parameter (T_N) were specified beforehand and these parameters served to terminate the algorithm when either one of the conditions was met.

2. Applying spatial compactness function in Simulated Annealing

After finding an appropriate annealing schedule for Simulated Annealing, four values of compactness factor, that is, 25, 50, 100 and 200, were applied in solving the same MOLAA problem. The cost function after incorporating the compactness function was calculated using Equation 3.12. The impact on spatial compactness and cost function was evaluated. In some runs, intermediate outputs were obtained to assess the progression of land use allocation by the algorithm. The spatial compactness was measured in terms of the number of patches at the land use level and landscape level using FRAGSTAT software. The lower number of patches indicated higher compactness and the higher number of patches implied relatively less compact. The performance of simulated annealing for all these cost models is discussed in Chapter 7.

3. Running Simulated Annealing

A program *'siman2d.exe'* (Leahy, 2004) was written in C++ based on the procedure illustrated in Figure 3.4. The program can run the algorithm in Mode 1, Mode 2 and Mode 3 with cooling functions as given by Equations 3.6, 3.8 and 3.9 in Chapter 3, respectively. The command line for running the algorithm in Mode 1 is as follows.

```
C:\siman2d <control file> <Run Mode> <Initial Control Parameter>
   <Cooling Rate> <Final Control Parameter> <Number of Swaps>
   <Compactness Function> <Dump Every>
```

Where simand2d implies '*siman2d.exe*', and control file specifies the input grids and their area requirement. Run Mode specifies the cooling function in Mode 1. Initial control parameter, cooling rate, final control parameter are the elements of the annealing schedule for the algorithm. Number of Swaps is any integer number assigned for swapping cells per control parameter step. Compactness function rewards the same land use by specified value; and Dump Every specifies production of land use and cost outputs at specified interval of iterations. The program produces two output maps for a final solution, that is, the land use and cost suitability maps. If the 'Dump Every' is specified at more than zero (an integer value), the output maps are also produced at every interval. The output result may also be saved as a text file which summarises each iteration step with the numbers of cold-swaps, hot-swaps and non-zero swaps and the cost function (see Annex 1).

If the program was run in Mode 2 and Mode 3, it did not require <Cooling Rate> but the number of iterations needed to be specified. For these modes, the run command became as follows.

```
C:\siman2d <control file> <Run Mode> <Initial Control Parameter>
   <Number of iterations> <Final Control Parameter> <Number of
   Swaps> <Compactness Function> <Dump Every>
```

In order to find an appropriate annealing schedule and cost models for solving a MOLAA problem by simulated annealing, three initial control parameters, three cooling functions, four cooling rates for the cooling function in Mode 1 and four swapping rates were tested. To select the appropriate cooling function, three cooling functions as given by Mode 1, 2 and 3 were applied by using the equivalent annealing schedules. The small grid size (10 by 10 cells) was found to be too small to compare the cost minimization by different annealing schedules. Hence, the medium (100 by 100 cells) and large (525 by 525 cells) grid sizes of the ordinal cost model were chosen for comparing the results by different annealing schedules in order to find appropriate parameters for Simulated Annealing.

In the command line discussed above, Simulated Annealing also requires values for 'Compactness Function' and 'Dump Every'. These parameters were not applied and 'zero' value was used instead during searching for the appropriate annealing schedule for simulated annealing.

5.5.2.3 Applying Tabu Search algorithms

1. Determining the parameters for Tabu Search

The descriptions of the search space, objective function and neighbourhood generation mechanism were the same for Tabu Search as for Simulated Annealing described in the previous section of this chapter. The following section describes other parameters specific to Tabu Search in the context of its application to a MOLAA problem.

I. Tabu length

The location of two swapping cells was recorded in the Tabu list in order to restrict cycling of the move for specified Tabu length. The minimum Tabu length could be set to 10 and the maximum Tabu length could be as high as 25 percent of a grid size in the program written for this algorithm. For assessing the impact of Tabu length on improving the cost function, different values of Tabu length were tested to find the best Tabu length for different grid size MOLAA problems. The influence of different Tabu length on the cost function is discussed in Chapter 8.

II. Neighbourhood solution generation

As in Simulated Annealing, the interchange or swap method was used for generating a new solution at each iteration. However, Tabu Search uses the following three neighbourhood structures:

Single neighbourhoods: After selecting the initial land unit (current cell), a subsequent selection of another land unit was made randomly and the costs of these two land units were compared for swapping. The swapping of land use took place, to ascertain whether the cost of the later land unit was cheaper than the former land unit or not. This process was repeated for a specified number of swaps per iteration. The random selection of land unit could select any one-land unit in the grid.

Four neighbourhoods: In four neighbourhoods, four land units were randomly selected in each iteration in order to find an appropriate cell for swapping with the initial land unit (current cell). The costs of the four cells chosen were compared and the land use of the cell with the lowest cost was swapped with the current cell. The same swapping rule was used as discussed above. This process was repeated for a specified number of swaps per iteration.

Eight neighbourhoods: In eight neighbourhoods, eight cells were randomly selected and their costs were compared for swapping with the current cell. The cell with the lowest cost was chosen and the land use was swapped with the current cell.

The number of neighbourhoods to be applied in the algorithm must be specified in the command line. As in Simulated Annealing, the same meaning of cold-swap and hot-swap applies in the Tabu Search algorithm. However, Tabu Search accepts every hot-swap, if the condition allows the swapping of the land use between the current cell with the cell with the lowest cost in the neighbourhood cells. In order to decrease the number of hot-swaps in the consecutive steps, the number of hot-swap acceptances was restricted to the ratio of the number of swaps per iteration divided by iteration step as given by Equation 5.7. For instance, in a run with 9619 swaps per step, the number of potential hot-swap acceptances for the 20th steps. In the first step, the potential hot-swap is equal to the number of swaps, that is, 9619. In the subsequent steps, the potential hot-swaps become 4809, 3206, 2405 in second, third and fourth step, respectively and so on. In this example, to reduce the potential hot-swaps to 1, the algorithm requires 9619 steps. If the higher number of swaps per step is applied to run the algorithm, the number of steps grows by the same number to reduce the potential hot-swap to 1. Therefore, to restrict such a huge number of steps, the minimum number of potential hot-swaps was set to five percent of the number of the swaps per step. For a run with 9619 swaps per step, the minimum number of potential hot-swap will be 480 and the algorithm reaches in the 19th steps. At the 20th steps, the potential hot-swap becomes zero and only cold-swaps are accepted.

$$\textit{Potential Hot-swaps} = int\left[\frac{1}{\text{Swapping Rate}\big/\text{No. of Steps}}\right] \qquad \text{Equation 5.7}$$

III. Number of swaps per iteration

Two different options for number of swaps per iteration were used. The specification of Mode number, either 1 or 2 in the run command, determined whether the static or dynamic option was to be used. Mode 1 employed the static option and a specified number of swaps per iteration took place. When Mode 2 was used, the dynamic option was applied. In this case, the number of swaps per iteration was determined randomly between the specified number of swaps and twice its value for each iteration. Four swapping rates as found by the 1, 10, 50 and 100 times the valid cells in the grid were applied in both modes.

IV. Stopping rule

In Tabu Search, the number of iterations was not specified so this process could continue indefinitely. The algorithm should not be terminated as long as there is some improvement in the cost function. Hence, a stopping rule was incorporated in the algorithm to terminate when there was no further improvement in the cost function throughout an iteration.

2. Applying compactness function in Tabu Search

The same four values of compactness factors, that is, 25, 50, 100 and 200 as in Simulated Annealing were applied in Tabu Search at the appropriate setting of parameters. Equation 3.12 estimated the cost function after every swapping of land uses. The influence of this algorithm using compactness function was compared with Simulated Annealing in terms of the spatial compactness and cost function. The results are discussed in Chapters 8 and 9.

3. Running Tabu Search

A program '*taboo.exe*' (Leahy, 2005) was written in C++ for the Tabu Search algorithm based on the procedure illustrated in Figure 3.5. The command line for executing the program in C prompt in MS dos is given below.

```
C:\taboo <control file> <Run Mode> <Tabu length> <Neighbour
   size> <Number of Swaps> <Compactness> <Dump Every>
```

Where taboo implies '*taboo.exe*', control file specifies the input grids and their area requirement, Run Mode 1 or 2 determines whether to use a static or dynamic option for the number of swaps per iteration, Neighbour size 1, 4 or 8 implies all neighbours, four neighbours or eight neighbours, respectively; Number of Swaps is any integer number assigned for swapping cells per iteration; Compactness rewards the same land use by specified value; and Dump Every specifies the production of land use and cost output at specified intervals of iteration. The program produces two output maps for the final and intermediate outputs similar to the Simulated Annealing. The output result from the program may also be saved as a text file which summarises each iteration step with the number of potential hot-swaps, cold-swaps and hot-swaps and the cost function (see Annex 2).

Tabu Search was implemented for three different grid sizes with three cost models. Different combinations of parameters were used to identify the appropriate value for each parameter. The optimum solutions generated by Tabu Search were compared with the solution by Simulated Annealing and GIS-based MOLA in IDRISI®.

5.6 Summary

A hypothetical MOLAA problem was designed in the Kioloa region of NSW for comparing the performance of these three methods. Four land uses were identified in order to accomplish six land use objectives. Altogether 17 criteria were used to derive land use suitability for these land use types. The criteria maps were used in the ordinal, continuous and fuzzy scales and combined by using the Weighted Linear Combination method. For the combinatory methods, these land use suitability models were transferred into cost models. The cost models were used to create initial input solution for applying the combinatory methods, using the random, cheapest and greatest difference methods.

The MOLA module was applied to the ordinal and continuous land use suitability models. The combinatory methods were applied to all three models including fuzzy cost model and three initial input solutions. The results are presented in Chapters 6, 7 and 8 for the MOLA module, Simulated Annealing and Tabu Search, respectively.

Chapter 6

RESULT AND DISCUSSION I - APPLYING MOLA IN SOLVING A HYPOTHETICAL MOLAA PROBLEM

This chapter reports the results of multi-objective land use allocation applying the MOLA module in IDRISI® software to a hypothetical MOLAA problem. Land use suitability models derived by the ordinal-WLC and continuous-WLC were used in the module (described in Chapter 5). In order to assess the land use conflicts among multiple land uses, this chapter first presents the ideal land use allocation for a single land use obtained from the MCE (Multi Criteria Evaluation) module in the same software. Then it follows the results of land use allocation for a hypothetical MOLAA problem in three grid sizes. A detailed analysis of the results was carried out for the small grid problem. This is followed by a discussion of the results and the technique itself.

6.1 Results

6.1.1 Solving a hypothetical MOLAA problem using MOLA

6.1.1.1 Land use allocation for the ordinal land use suitability model

Figure 6.1 displays the allocation of four land use types in the Kioloa region by MOLA using the ordinal land use suitability model. The module was run twice with zero tolerance. On both occasions, the final land use allocations were delivered in less than a minute of run time after 38 passes. In contrast to spatial allocation of these land uses, both these runs confirmed exactly the same land use allocation for each land unit. A summary of the results produced at the end of each MOLA operation is given in Annex 3 which provides the cut, goal and number of cells achieved in each pass. The cut values in the final pass provide the highest rank cell allocated to each land use type to achieve the area requirements. The allocation of 18,611 units to development land use was met from a maximum rank value of 33,663. The requirement of 27,918 cells for forestry land use was fulfilled from the lowest suitability ranking of 36,247. Agricultural land use was allocated to 46,530 out of 81,001 ranking cells. In the case of conservation land use, the allocation of 93059 land units was achieved by assigning the land unit with the lowest suitability ranking, that is, rank value of 186118. The spatial compactness in terms of number of patches as defined by the four-neighbourhood and eight-neighbourhood rules was found to be 8,665 and 4,862, respectively. The lower number of patches indicates a higher level of spatial compactness (discussed in Chapter 5). Table 6.1 presents the maximum rank values for meeting the area requirements and spatial compactness values for each land use type.

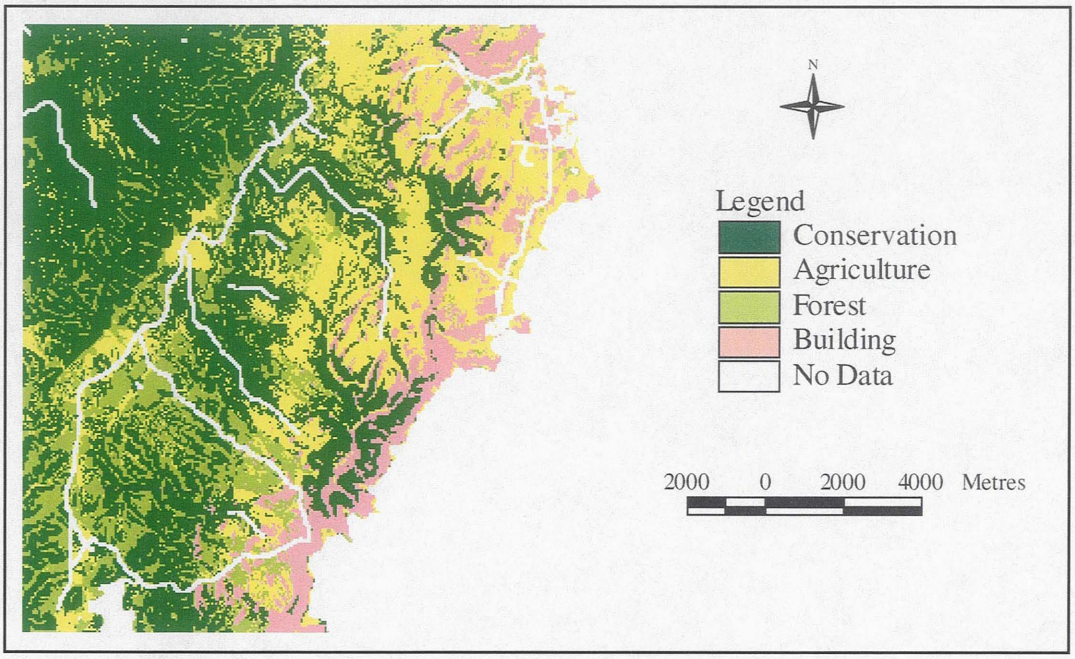


Figure 6.1 Land use allocation for the Kioloa region by MOLA using ordinal land use suitability model

Table 6.1 Rank values and spatial compactness for ordinal land use suitability model

SN	Land use	No of cells required	Maximum rank values	Spatial compactness	
				4-neighbours	8-neighbours
1	Conservation	93,059	186,118	1,800	775
2	Agriculture	46,530	81,001	3,983	2,331
3	Forestry	27,918	36,247	2,109	1,314
4	Development	18,611	33,663	773	442
5	Total	186,110		8,665	4,862

A detailed analysis of a small grid of 10 X 10 cells with the same land use types and area requirements as in the Kioloa region revealed that the module assigns each land unit x with the most suitable land use k, by comparing the rank values for all the land use types. Figures 6.2 and 6.3 display the cell values in the suitability and rank maps for four land use types in the small grid. The first and second cells in the last column in the suitability map (Figure 6.2) were deemed unsuitable for development use due to the susceptibility of the areas to flood hazard. In the rank maps (Figure 6.3), these cells were assigned the lowest rank values, that is, 99 and 100 for development use.

The final land use allocation by the MOLA in two independent runs is shown in Figure 6.4 for the 10 by 10 grid. The rank value of the cells allocated to each land use in the final land use allocation is given in Table 6.2. In this small grid, the area requirement of 10, 15 and 25 cells for development, forestry and agriculture land uses were met by allocating the maximum rank values of 14, 19 and 62 respectively. The highest rank value to select 50 cells for conservation land use was 96. The numbers of patches for the four-neighbour rules were found to be 4, 7, 8 and 7 for conservation, agriculture, forestry and development land uses respectively (Table 6.2).

Table 6.2 Distribution of rank values allocated to four land uses in a small grid by MOLA using ordinal land use suitability model

SN	Land use No of cells required	Maximum rank values	Rank value distribution	Spatial compactness
1	Conservation 50	96	1, 3-7, 9-12, 14, 16, 18, 20, 23, 26-29, 31-33, 36, 43, 50-54, 56-59, 68, 70, 71, 73, 76, 78-81, 83,85, 87, 88, 90-92, 96	4
2	Agriculture 25	62	1-5, 8, 10-14, 16, 21, 24, 33, 40-42, 44, 45, 49, 54, 55, 60, 62	7
3	Forestry 15	19	1, 3-6, 8-14, 17-19	8
4	Development 10	14	1-3, 5, 9-14	7

Figure 6.2 Land use suitability maps with values for four land uses in the small grid. Black squares indicate NODATA values

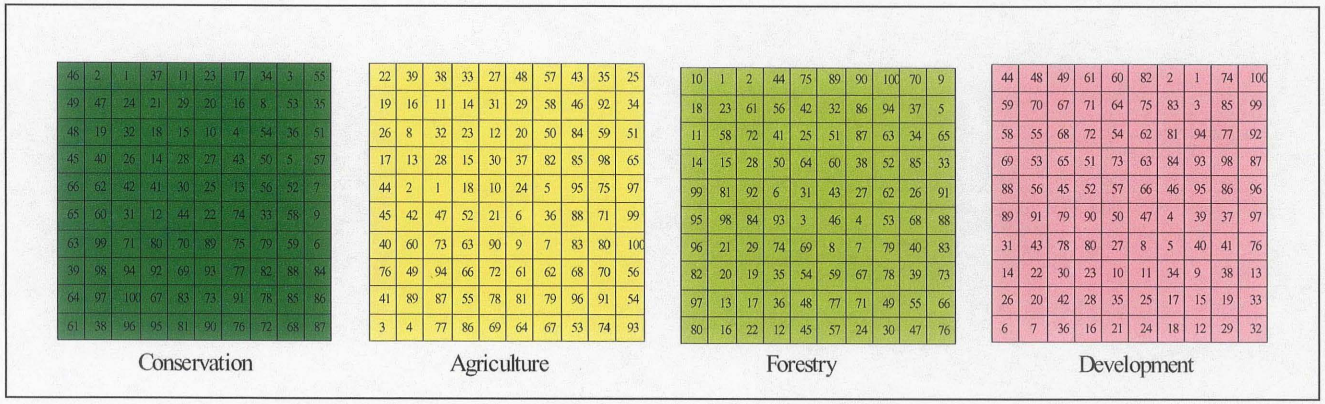


Figure 6.3 Rank maps with values for four land uses in the small grid

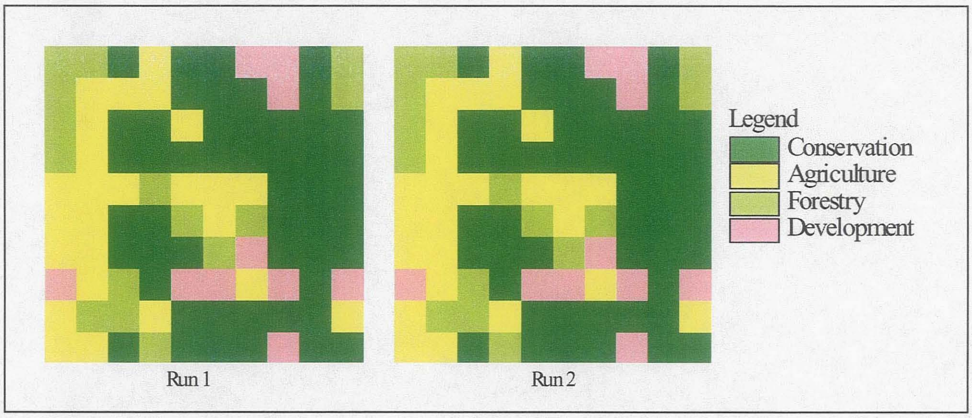


Figure 6.4 Land use allocation for the small grid of ordinal land use suitability model

6.1.1.2 Land use allocation for continuous land use suitability model

For the continuous land use suitability model, land use allocation with the same input variables as in the ordinal model took one minute 35 seconds to achieve the desired number of cells for each land use type, accomplished in 879 passes by the MOLA module (Figure 6.5). The cut values in the final pass were found to be 179,123, 86,037, 42,282 and 26,606, respectively for conservation, agriculture, forestry and development land uses. The spatial compactness was enhanced by about 25 percent in the continuous model. Table 6.3 presents maximum rank values for meeting the respective area requirement and spatial compactness values for each land use type in land use allocation for continuous model by MOLA.

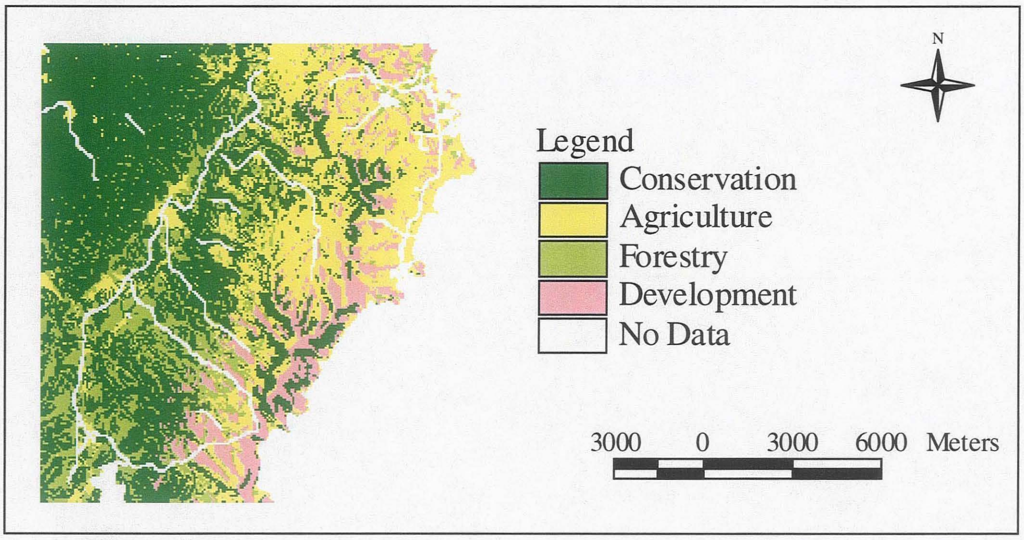


Figure 6.5 Land use allocation by MOLA for the continuous land use model

Table 6.3 Rank values and spatial compactness for continuous land use suitability model

SN	Land use	No of cells required	Maximum rank values	Spatial compactness	
				4-neighbours	8-neighbours
1	Conservation	93,059	179,123	1,479	691
2	Agriculture	46,530	86,037	1,990	1,069
3	Forestry	27,918	42,282	2,341	1,438
4	Development	18,611	26,606	773	450
5	Total	186,110		6,550	3,648

In the small grid of 10 X 10 cells, MOLA accomplished the allocation of four land uses in a few seconds with the same input parameters as in ordinal model. It took 19 passes to achieve the desired number of cells for each land use compared with 11 passes for the ordinal model. However, the lowest suitability value was improved for all these land uses for the continuous model (Table 6.4). Development land use was found to be the ideal land use allocation, receiving 10 cells out of 10 rank level. The total number of patches remained the same as in the ordinal model. However, there was an increase in the number of patches for the conservation land use, which was compensated by a decrease in the number of patches for the other three land uses (Table 6.4).

Table 6.4 Distribution of rank values for four land use types in a small grid for continuous land use suitability model

SN	Land use No of cells required	Maximum rank values	Rank value distribution	Spatial compactness
1	Conservation 50	84	1, 3-7, 9-15, 17, 19, 38-40, 42, 53-80, 82, 84	7
2	Agriculture 25	51	1-20, 23, 24, 27, 40, 51	6
3	Forestry 15	18	1, 4-11, 13-18	7
4	Development 10	10	1-10	6

6.2 Discussion

MOLA module was found to be biased towards the land uses with lower area requirements than land use with the highest area requirement. It means that the MOLA allocates the most suitable land units to the land uses with less area requirements. The analysis of cell values in the output showed that each cell was assigned with the land use with the lowest rank value, signifying the best suitable land use. This was accomplished by comparing the rank values among the land uses and the land use with the lowest rank value (higher suitability) was assigned to the land unit. In carrying out this operation, the land use types with the smaller area requirements were allocated with highly suitable land units, whereas the land use with highest area requirement was allocated all the remaining land units, regardless of their suitability. In this hypothetical problem, the land uses with smaller area requirements (development, forestry and agriculture) were met by comparatively highly suitable land units than the land use with the largest area (conservation). Conservation land use was allocated with less suitable land units, those not claimed by other land uses.

The module's preference to allocate highly suitable land units to the land use types with the smaller area requirement is controlled by the rank maps. The RANK operation transformed the suitability maps into the rank maps by ordering the suitability values based on the range, magnitude and number of discrete values in the suitability map of a particular land use. Though the rank map provides the suitability ranking of each land unit for a land use, the values in the rank maps for different land uses do not imply a relatively suitability ranking. This is because a land unit with the same suitability value for two different land uses is most likely to get different rank values by the ranking operation when the suitability maps have a different range and distribution of suitability values for these land uses. Even if a cell is less suitable in terms of relative suitability value in the suitability map for a land use, it may get a higher ranking order than a land use which has higher suitability value for that cell.

The transformation of the suitability value to rank value by the RANK operation is illustrated in Figures 6.2 and 6.3. In the suitability maps (Figure 6.2), the lower right cell in the 10 by 10 grid has a suitability value of 82, 130, 172 and 80 for conservation, agriculture, forestry and development land use, respectively. The forestry land use with the highest relative suitability value (172) among all the land uses was the most suitable land use for the cell. Agriculture land use was the second appropriate land use for the cell, followed by conservation land use. The development land use was the lowest suitability for that cell. However, the RANK operation resulted in rank values of 87, 93, 76 and 32 for these land uses, respectively (see Figure 6.3). Though the cell had the least suitable value for development land use, it was assigned the best rank value among the four land uses. The RANK operation distorted the relative suitability of the different use for a land unit by assigning a rank value, in order of suitability value, for a single land use.

The MOLA does not account for overall suitability and it allocates the same land use to each land unit in different runs using the same rank maps, area requirement and preferences of land uses. However, the module generates different land use allocation and spatial compactness for the land use suitability maps produced by using ordinal and continuous models. These differences in the land use allocation and spatial compactness can be attributed to the difference in the rank maps generated from the suitability models of these land uses with differences in the value, range, magnitude and spatial distribution. With the finer representation of the land use suitability in the continuous model than in the ordinal model, the MOLA module produced a more spatially compact land use allocation in the former model than in the latter.

One major advantage of the MOLA module is that it can allocate a specified number of cells to each land use based on the ranking maps. Similar to this module, UPOS, a grid function in ArcInfo®, can also combine several grids with suitability values and gives an output assigning the cell with the highest value among the grids. Preference for any land use can also be specified in the function, but this does not allow area requirement specification. A similar kind of operation could also be accomplished by writing an Arc Macro Language (AML) in ArcInfo® (Lees, 2004). Another GIS software called GIWIN (Geographic Information Workshop for Windows) was especially developed for land use planners and decision makers to introduce them to the capabilities of GIS and provide decision support in solving a MOLAA problem (Ren, 1997). This software is based on the same principle as the MOLA module in IDRISI®. GIWIN uses suitability values in the range 0-100 and directly employs the suitability maps for allocating the desired area to a specified land use. Both the MOLA module and GIWIN can provide decision support in solving a MOLAA problem. However, their efficiency in solving the same problem has not yet been compared.

6.3 Conclusion

Different rank maps derived from the land use suitability maps with different magnitudes and ranges do not truly represent the relative value among different land uses for a land unit. Hence, land use allocation by the MOLA module does not use relative suitability as a measure of allocating land use to a cell, rather, it tries to allocate each land use with the highest rank value. This resulted in a bias towards these land uses with lower area requirement by allocating more suitable land units to them.

Due to the inherent bias towards the land uses that require less area, the MOLA module could not optimise the allocation for all land uses desired by users or decision makers.

6.4 Summary

The MOLA module in IDRISI® was applied to a hypothetical MOLAA problem using the ordinal and continuous land use suitability models. A detailed analysis of the output found an inherent bias in this module towards those land uses with a smaller area requirement over land uses with a larger area requirement. The MOLA module tries to secure the most suitable land units to a single land use but fails to maximize overall land use suitability as it is unable to allocate land uses based on the relative suitability. The land use allocation and spatial compactness tend to vary between using the ordinal and continuous land use suitability models. However, the land use allocation was more spatially compact in the continuous land use suitability model compared with the ordinal model. Unlike the UPOS Grid function in ArcInfo® and the AML method, this module is capable of allocating the desired area to specified land uses but does not allow for improving the spatial compactness for more coherent land use allocation.

The following Chapters 7 and 8 will discuss the application of Simulated Annealing and Tabu Search to the same MOLAA problem, respectively. Chapter 9 presents a comparison of the MOLA module and two combinatory methods in terms of their performance in solving the same MOLAA problem.

Chapter 7

RESULT AND DISCUSSION II – APPLYING SIMULATED ANNEALING TO A HYPOTHETICAL MOLAA PROBLEM

This chapter presents the results of applying Simulated Annealing to the hypothetical MOLAA problem. The algorithm with different combinations of annealing parameters (discussed in Chapter 5) were applied to the three cost models (ordinal, continuous and fuzzy) with the random, cheapest and greatest difference initial input models (described in Chapter 5) in solving the MOLAA problem. The performance of the algorithm was evaluated, using the minimization of the cost function, spatial compactness and the computation time taken by the algorithm. Table 7.1 summarises the parameters, and provides a brief description and a null hypothesis relating to their specific influences on the cost function minimization or spatial compactness in solving a MOLAA problem.

Table 7.1 A summary of the parameters, their descriptions and hypothesis

Parameters	Brief description	Null Hypothesis
Cooling Function	A function used to cool down the initial control parameter - it affects the pattern of reduction in the initial control parameter and the number of iteration required.	The minimization of the cost function does not differ significantly among the three cooling functions.
Initial Control Parameter	Initial value on which cooling takes place by the specified rate in each step - it affects the level of acceptance of higher cost functions and hence determines the capacity for avoiding local minima.	The improvement of the cost function does not differ significantly among different values of initial control parameter.
Cooling rate	A fixed rate at which initial control parameter is reduced in each step - it controls the speed of the algorithm by determining the number of iterations step.	The minimization of the cost function does not differ significantly among the cooling rates.
Swapping rate	Number of exchanges of land uses allowed between two land units in each step - it affects the cost minimization by controlling the number of cold-swaps and hot-swaps.	The minimization of the cost function does not differ significantly among the swapping rates.
Compactness function	A function that takes into account of the land uses in the four neighbours of the selected cells - it affects the compactness by rewarding a move that increases the spatial compactness.	The spatial compactness does not differ significantly among the different values of the compactness factor.
Initial input solution	Initial solutions generated by random, cheapest and greatest difference methods – the initial solution may influence the output and performance of the algorithm.	The minimization of the cost function does not differ significantly among three initial input solutions.
Cost model	Suitability models derived from the criteria maps using ordinal, continuous and fuzzy-WLC method - the models may influence on the output and performance of the algorithm.	The spatial compactness does not differ significantly among three cost models.

7.1 Results

7.1.1 Determining initial control parameter for Simulated Annealing

The hot-swap acceptance percentages of 50, 80 and 98 in the first cooling step were used to find low, medium and high values of initial control parameters (T_1) for different datasets (discussed in Chapters 3 and 5). Tables 7.2 and 7.3 depict the values of initial control parameters at 50, 80 and 98 percent of hot-swap acceptance for all three grid sizes and initial input solutions (random, cheapest and greatest difference) of the ordinal and continuous cost models, respectively. In the case of the fuzzy cost model, these values were found to be relatively higher than in the ordinal and continuous cost models. However, the same values of initial control parameter were found for all three initial input solutions in the fuzzy model. The initial control parameters for fuzzy model are given in Table 7.4.

Table 7.2 Initial control parameters for ordinal model at different hot-swap acceptance percentages

S. N.	Grid size	Initial Input Solution								
		Random			Cheapest			Greatest difference		
		50%	80%	98%	50%	80%	98%	50%	80%	98%
1	Small	175	600	10000	170	550	10000	170	550	1000
2	Medium	325	1125	13000	315	1100	13000	325	1100	14000
3	Large	360	1250	15000	360	1250	15000	365	1250	15000

Table 7.3 Initial control parameters for continuous model at different hot-swap acceptance percentages

S. N.	Grid size	Initial Input Solution and hot-swap acceptance %								
		Random			Cheapest			Greatest difference		
		50%	80%	98%	50%	80%	98%	50%	80%	98%
1	Small	300	1000	12000	300	1100	11500	325	1200	12500
2	Medium	375	1300	16000	385	1375	17000	400	1375	17000
3	Large	500	1800	20000	475	1725	22000	500	1800	20000

Table 7.4 Initial control parameters for fuzzy model at different hot-swap acceptance percentages

S.N.	Grid size	Initial input parameter at hot-swap acceptance %		
		50%	80%	98%
1	Small	1500	4800	45000
2	Medium	3000	11000	125000
3	Large	3700	13000	145000

7.1.2 Cooling function for Simulated Annealing

In order to find the best cooling functions for solving a MOLAA problem, three cooling functions as given by Modes 1, 2 and 3 (described in Chapter 5) were compared for improving the cost function using the medium grid of ordinal cost model. Table 7.5 summarizes the annealing schedules and corresponding mean cost functions by the algorithm in Modes 1, 2 and 3. The algorithm in Mode 1 produced the maximum improvement in the cost function, achieving the lowest values of mean cost functions for all the annealing schedules. The algorithm in Mode 2 improved the cost function slightly more than in Mode 3. Figures 7.1 and 7.2 illustrate the distribution of cost functions, their mean values and ranges in Mode 1 and compare them with Mode 2 and Mode 3 at a very slow cooling rate.

The improvement in the cost function in Mode 1 was found to be significantly different from the mean cost functions of Modes 2 and 3 at 95 percent confidence interval. Thus the null hypothesis was rejected about the same influence of these three Modes on the cost function minimization (see Table 7.1). In the large grid, these cooling functions had the same influence on the cost function minimization as in the medium grid. Because of the significant improvement in the cost function in Mode 1, this cooling function was chosen for further investigation of the application of Simulated Annealing in solving a MOLAA problem.

Table 7.5 Mean cost functions at different annealing schedules in Modes 1, 2 and 3 for the medium grid of ordinal cost model

Total Cost Function (C_F) = 4153000 +

Swapping rate	Very fast cooling rate (C_R) = (0.2)					Fast cooling rate (C_R) = (0.5)				
	T_I	N_{CS}	Mode 1 C_F	Mode 2 C_F	Mode 3 C_F	T_I	N_{CS}	Mode 1 C_F	Mode 2 C_F	Mode 3 C_F
9619	H	71	3375	403692	505624	L	90	2457	35839	42301
96190	L	29	1043	10574	5232	L	31	1030	10169	14881
480950	H	17	860	5322	15561	M	19	870	4335	5042
961900	H	13	833	2121	2172	M	16	824	2004	2087
Swapping rate	**Slow cooling rate (C_R) = (0.8)**					**Very slow cooling rate (C_R) = (0.98)**				
	T_I	N_{CS}	Mode 1 C_F	Mode 2 C_F	Mode 3 C_F	T_I	N_{CS}	Mode 1 C_F	Mode 2 C_F	Mode 3 C_F
9619	L	97	2427	33420	39883	M	331	1847	35363	40717
96190	M	46	1039	18687	27991	L	277	827	2314	2331
480950	M	37	827	3603	4340	L	289	752	970	2331
961900	M	36	794	1830	2013	M	355	732	1007	1050

Note: The algorithm minimized the cost function better in the Mode 1 than in the Modes 2 and 3.

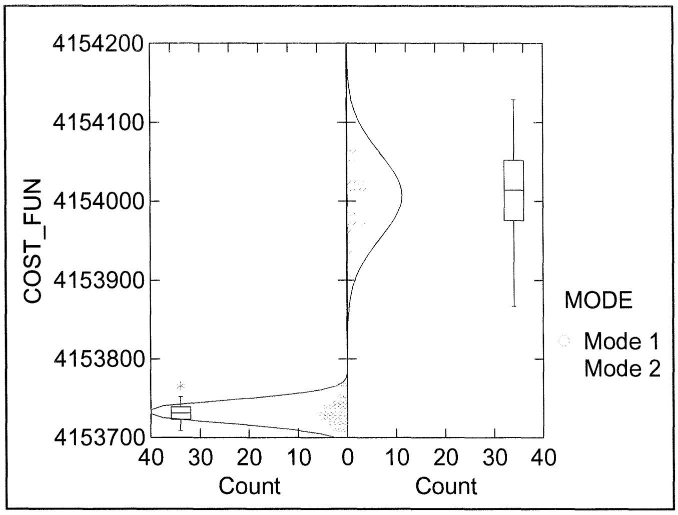


Figure 7.1 Comparison of cost functions at very slow cooling rates in Mode 1 with Mode 2

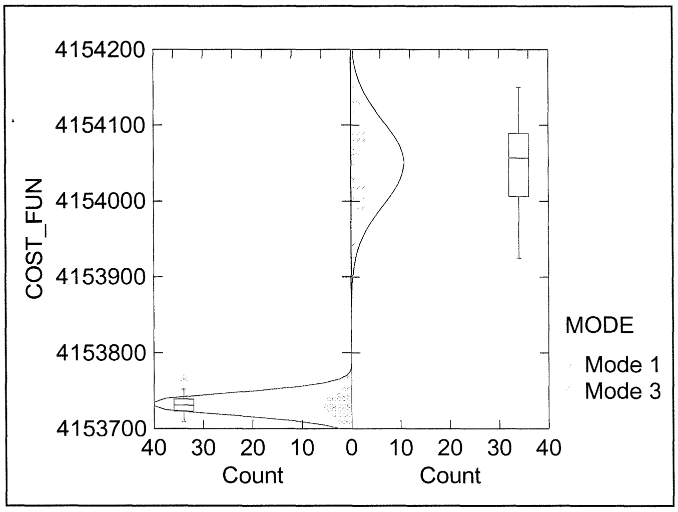


Figure 7.2 Comparison of cost functions at very slow cooling rates in Mode 1 with Mode 3

7.1.3 Cost function minimization by different parameters

The minimization of the cost function was actually brought about by a combination of initial control parameter, cooling rate and number of swaps per step used in the annealing schedule in Mode 1 cooling function. The influence of these parameters on cost minimization will be investigated by applying the algorithm in the random input solution of ordinal cost model in the medium grid MOLAA problem.

7.1.3.1 Influence of initial control parameter on cost function

Table 7.6 presents the mean cost functions at low, medium and high values of initial control parameter, at three values of cooling rate and four values of number of swaps per control parameter step for the medium grid of the ordinal cost model. The statistical test at 95 percent confidence interval did not find any significant difference among these mean cost functions at the three values of initial control parameter, except for one case. The mean cost functions at the low value of initial control was found to be significantly different from the mean at the medium value. The significantly different mean cost functions are indicated by superscript (^{M}) in Table 7.6.

Table 7.6 Mean cost function at low, medium and high values of initial control parameters (T_I) for medium grid of ordinal cost model

Total Cost Function (C_F) = 4153000 +

Swapping rate	Very fast cooling rate (0.2)			Fast cooling rate (0.5)		
	Low T_I	Medium T_I	High T_I	Low T_I	Medium T_I	High T_I
9619	3397	3433	3375	2457	2552	2544
96190	1043^{M}	1094	1066	1030	1076	1044
480950	869	883	860	876	870	878
961900	838	842	833	825	824	834
Swapping rate	**Slow cooling rate (0.8)**			**Very slow cooling rate (0.98)**		
	Low T_I	Medium T_I	High T_I	Low T_I	Medium T_I	High T_I
9619	2427	2625	2604	1874	1847	1847
96190	1062	1039	1066	827	834	828
480950	830	827	835	752	759	756
961900	801	794	798	738	732	733

Note: The mean cost functions were not significantly different among three values of initial control parameter except for one case shown by superscript (^{M}).

The significant difference of mean cost function in only one case out of 64 comparisons was not found adequate to reject the original hypothesis regarding the influence of initial control parameter on the cost function minimization (see Table 7.1). Thus, the hypothesis was accepted.

7.1.3.2 Influence of cooling rate (C_R) on the cost function

Four cooling rates with reduction factors, 0.2, 0.5, 0.8 and 0.98, were applied in the annealing schedules. The mean cost functions for thirty runs at these cooling rates at the high value of initial control parameter and four values of swapping rates are presented in Table 7.7. The very slow (C_R) = (0.98) cooling rate produced the lowest mean cost function for all combinations of annealing schedules. The variation in the cost function at different runs with the same annealing schedule decreased from the very fast cooling rate (C_R) = (0.2) to the very slow cooling rate (C_R) = (0.98). These mean cost functions were statistically tested for significance difference at 95 percent confidence interval. The mean cost functions significantly different from the mean at other cooling rates, are indicated by superscript. It implies that the algorithm did not produce the same result for the cost minimization at different cooling rates. Hence, the null hypothesis was rejected.

Table 7.7 Cost function at very fast, fast, slow and very slow cooling rates for medium grid of ordinal cost model

Total Cost Function (C_F) = 4153000+

Swapping rate	Cost function at cooling rates			
	Very fast	Fast	Slow	Very slow
9619	$3375^{F,S,VS}$	$2544^{VF,VS}$	$2604^{VF,VS}$	$1847^{VF,F,S}$
96190	1066^{VS}	1044^{VS}	1066^{VS}	$828^{VF,F,S}$
480950	860^{VS}	878^{VS}	835^{VS}	$756^{VF,F,S}$
961900	$833^{S,VS}$	$834^{S,VS}$	798^{VS}	$733^{VF,S,F}$

Note: The mean cost functions were found to be significantly different at different cooling rates and the significant difference means were shown by superscript indicating very fast, fast, slow and very slow cooling rates by VF, F, S, and VS, respectively.

The improvement in the cost function against the cooling steps at these cooling rates is illustrated in Figure 7.3, applying the swapping rate (S_R) = (100*V_C) and high value of initial control parameter. The cost function was minimized quickly (in less than 70 control parameter steps) at the very fast, fast and slow cooling rates whereas the very slow cooling rates took more than 450 control parameter steps to minimize the cost function.

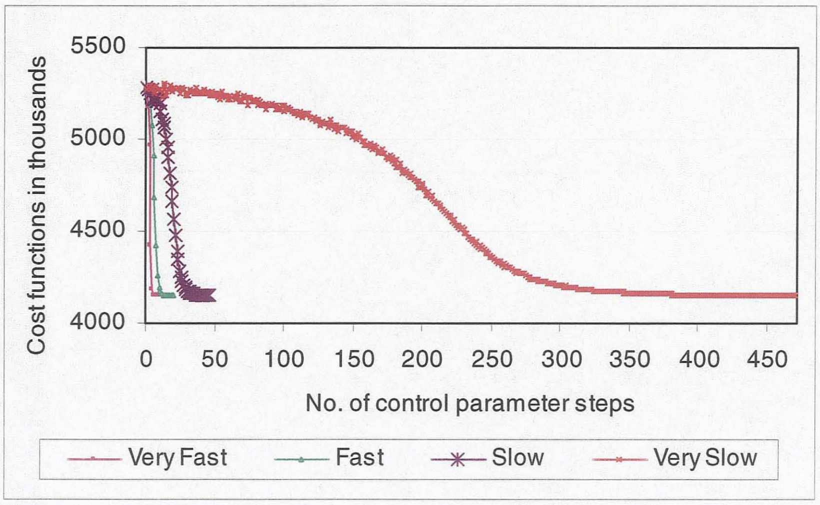


Figure 7.3 Improvement in the cost function at different cooling rates

The cooling rates determined the number of cold-swaps and hot-swaps acceptances in the algorithm. The number of cold-swaps and hot-swaps at different cooling rates are illustrated in Figures 7.4 and 7.5, respectively. The higher number of hot-swaps was accepted with the slower cooling rates from the very fast to very slow cooing rates. The number of cold-swaps was controlled by the hot-swap acceptances. However, the algorithm accepted a slightly higher number of cold-swaps than the hot-swaps for every control parameter step at all cooling rates. After the hot-swaps became zero, the algorithm accepted only a few cold-swaps and terminated after a couple of control parameter steps meeting the stopping criterion at which the cold-swaps became zero.

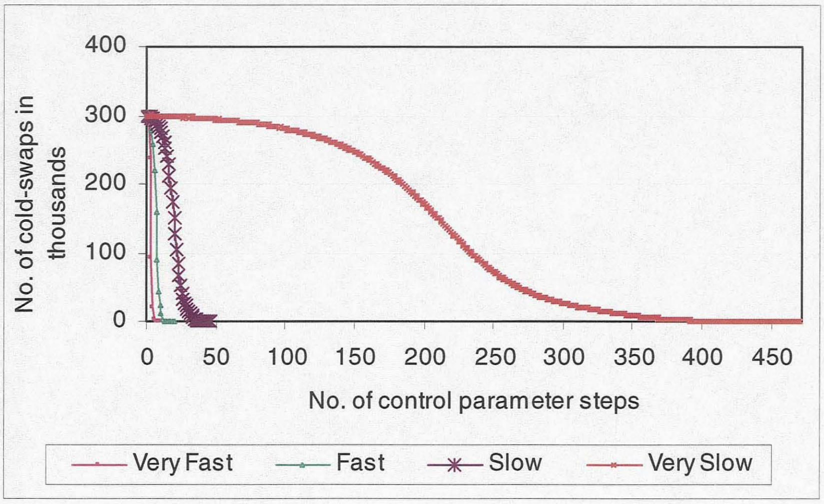


Figure 7.4 Accepted number of cold-swap at different cooling rates

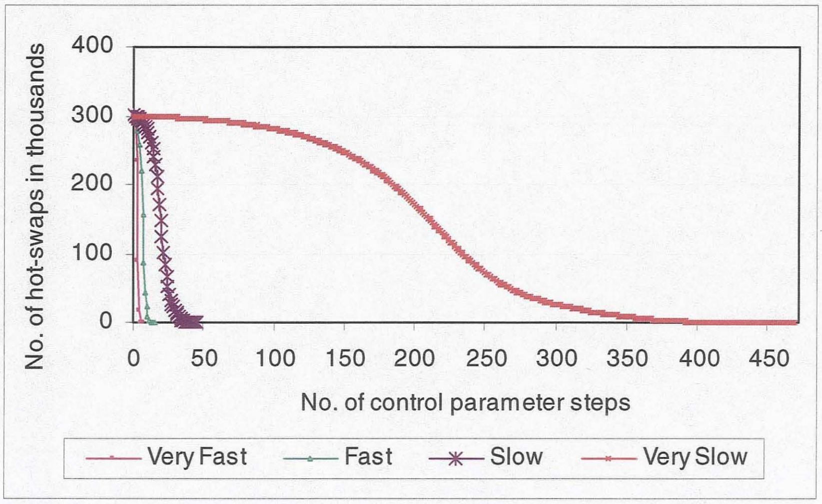


Figure 7.5 Accepted number of hot-swaps at different cooling rates

The total numbers of cold-swaps and hot-swaps accepted depend on the number of cooling or control parameter steps. In Mode 1 cooling function, the cooling rate was found to determine the number of cooling steps for the same values of initial control parameters and the swapping rate. The number of control parameter steps at different cooling rates is shown in Figure 7.6 for four swapping rates. Among the cooling rates, the number of control parameter steps (cooling steps) was found to increase from a very fast cooing rate to a very slow cooing rate for the same value of initial control parameter and swapping rate.

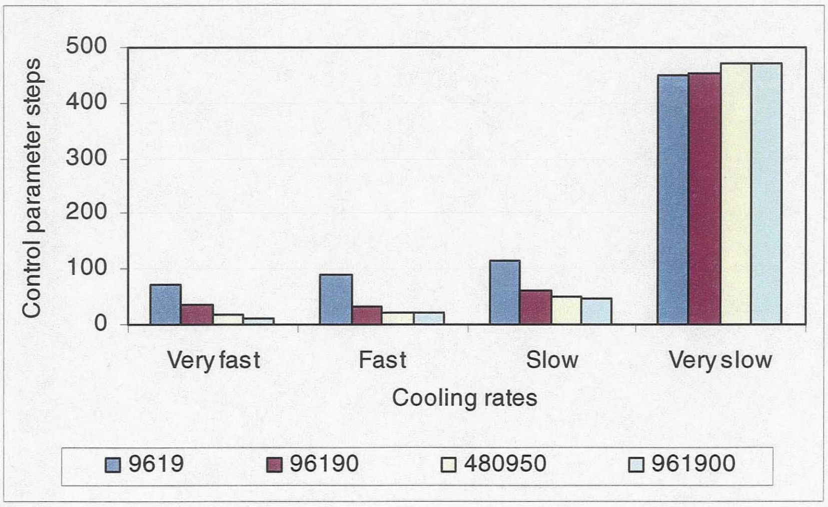


Figure 7.6 Number of control parameter steps at different cooling rates

7.1.3.3 Influence of swapping rate (S_R) on the cost function

The swapping rate (S_R) determined the number of swaps per control parameter step. The influences of four swapping rates (as multiples of one, ten, fifty and one hundred times the valid cells in the input grid) in the annealing schedule were assessed by their role in improving the cost function. The influences of these swapping rates (S_R) = ($1*V_C$), ($10*V_C$), ($50*V_C$) and ($100*V_C$) are displayed at the high value of initial control parameter using four cooling rates (C_R) = (0.2, 0.5, 0.8 and 0.98) in Figure 7.7.

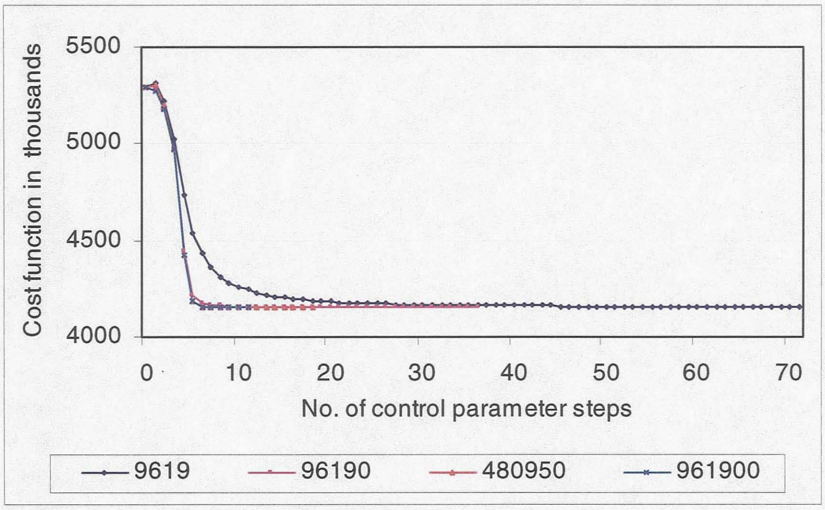


Figure 7.7 Cost function minimization by four different swapping rates at very fast cooling rate and high value of initial control parameter

The lowest swapping rate (S_R) = ($1*V_C$) and the highest swapping rate (S_R) = ($100*V_C$) produced a minimal and maximum improvement in the cost function for all the cooling rates and initial control parameters, respectively. At the higher number of swaps (S_R) = >=($50*V_C$), the large numbers of hot-swaps and cold-swaps were accepted at all cooling rates. Thus, the highest improvement in the cost function was achieved at all cooling rates by reducing the differences in the cost function at these cooling rates for all values of initial control parameters. The mean cost functions were found to be significantly different between the swapping rate (S_R) = ($50*V_C$) and (S_R) = ($100*V_C$) at 95 percent confidence intervals. Therefore, the findings did not support the null hypothesis (see Table 7.1) and it was rejected.

7.1.4 Optimum cost function for different cost models

Among three initial input models, the random and greatest difference initial input solutions had the highest and lowest value of cost function in the initial input solution (see Chapter 5). Hence the greatest difference and random input solutions were chosen for estimating the near-optimum cost function. The annealing schedule, run time, cost functions and spatial compactness for random and greatest difference initial input solutions are given for all three grids of the ordinal, continuous and fuzzy cost models in Tables 7.8, 7.9 and 7.10, respectively.

Table 7.8 Cost functions closest to the global cost functions for all three grids of ordinal cost model

S. N.	Grid size	Annealing schedule C_R	T_I	S_R	Run time h:m	Near optimum C_F	C_F Reduction %	No of patches N_P	Change in N_P
Random initial input solution									
1	Small	0.2	L	10,000	<0:01	40910	12.981	17	- 10
2	Medium	0.98	H	2,885,700	1:34	4153709	21.500	352	-1645
3	Large	0.98	H	55,835,400	62:15	68283447	26.990	4105	- 34739
Greatest difference initial input solution									
1	Small	0.2	L	10,000	<0:01	40752*	10.029	15	+ 6
2	Medium	0.98	H	2,885,700	1:33	4153450	8.954	375	+ 152
3	Large	0.98	H	55,835,400	61:14	68283150	10.935	4115	- 267

Table 7.9 Cost functions closest to the global cost functions for all three grids of continuous land use suitability model

S. N.	Grid size	Annealing schedule C_R	T_I	S_R	Run time h:m	Near optimum C_F	C_F Reduction %	No of patches N_P	Change in N_P
Random initial input solution									
1	Small	0.2	L	10,000	<0:01	75850*	15.508	9	- 7
2	Medium	0.98	H	2,885,700	3:26	7512893	16.219	281	- 1724
3	Large	0.98	H	55,835,400	68:28	129697574	21.901	3365	- 35608
Greatest difference initial input solution									
1	Small	0.2	L	10,000	<0:01	75850	5.317	9	+ 4
2	Medium	0.98	H	2,885,700	3:44	7512273	8.099	281	- 43
3	Large	0.98	H	55,835,400	60:34	129698148	19.033	3373	- 2569

Table 7.10 Cost functions closest to the global cost functions for all three grids of fuzzy land use suitability model

S. N.	Grid size	Annealing schedule C_R	T_I	S_R	Run time h:m	Near optimum C_F	C_F Reduction %	No of patches N_P	Change in N_P
Random initial input solution									
1	Small	0.2	L	10,000	<0:01	249764	19.291	11	- 14
2	Medium	0.98	H	2,885,700	1:58	29615668	27.493	285	+ 109
3	Large	0.98	H	55,835,400	61:23	451317514	36.451	3149	- 35554
Greatest difference initial input solution									
1	Small	0.2	L	10,000	<0:01	248292*	5.621	12	+ 4
2	Medium	0.98	H	2,885,700	2:00	29612198	18.970	300	- 26
3	Large	0.98	H	55,835,400	70:05	451317534	23.036	3146	- 1197

Note: The symbol * indicates the optimum cost function.

In the small grid, the cost functions in the greatest difference initial input solution were not more improved over the values given in these Tables for all cost models. These cost functions were taken as the optimum (global) cost function for respective grid size, initial input solution and cost model. In all cost models, these optimal cost functions for the small grid were achieved in the annealing schedule with (C_R, T_I, S_R) = (0.2, low, 100*V_C) in less than one minute running time. The near-optimal cost functions for the medium and large grids were obtained by applying the algorithm with the annealing schedule (C_R, T_1, S_R) = (0.98, high, 300*V_C). Even the higher value of swapping rate (S_R) = (>300*V_C) did not improve the cost function significantly more than the swapping rate (S_R) = (300*V_C). Therefore, the cost functions obtained by the annealing schedule with (C_R, T_1, S_R) = (0.98, high, 300*V_C) were taken to be the closest to the global optimum and were used for comparing the performance of the algorithm under different annealing schedules.

The optimum or near optimum cost functions for the small and medium grids were found smaller in the greatest difference initial input solution than the random input solution for all cost models. However, the cost functions were smaller in random initial input solution for large grids of continuous and fuzzy cost models. This implies that the algorithm could improve the cost function better in the random initial input solution than in the greatest difference initial input solution at the higher swapping rate (S_R) = (=>300*V_C). The random initial input solution and near-optimal land use allocation to the MOLAA problems are shown in Figure 7.8 for the small, medium and large grids.

Tables 7.8 to 7.10 also present the percentage reductions in the cost functions calculated from the initial cost function for the respective initial input solutions. Among the cost models, the algorithm reduced the cost function to its maximum in fuzzy cost models and this was followed by the ordinal cost models for the random initial input solution. Along with the cost function minimization, the algorithm produced fewer patches in the final solution than in the random initial input solution, resulting in a spatially compact land use allocation. In some cases, the number of patches was higher in the near-optimal solution than in the greatest difference initial input solution.

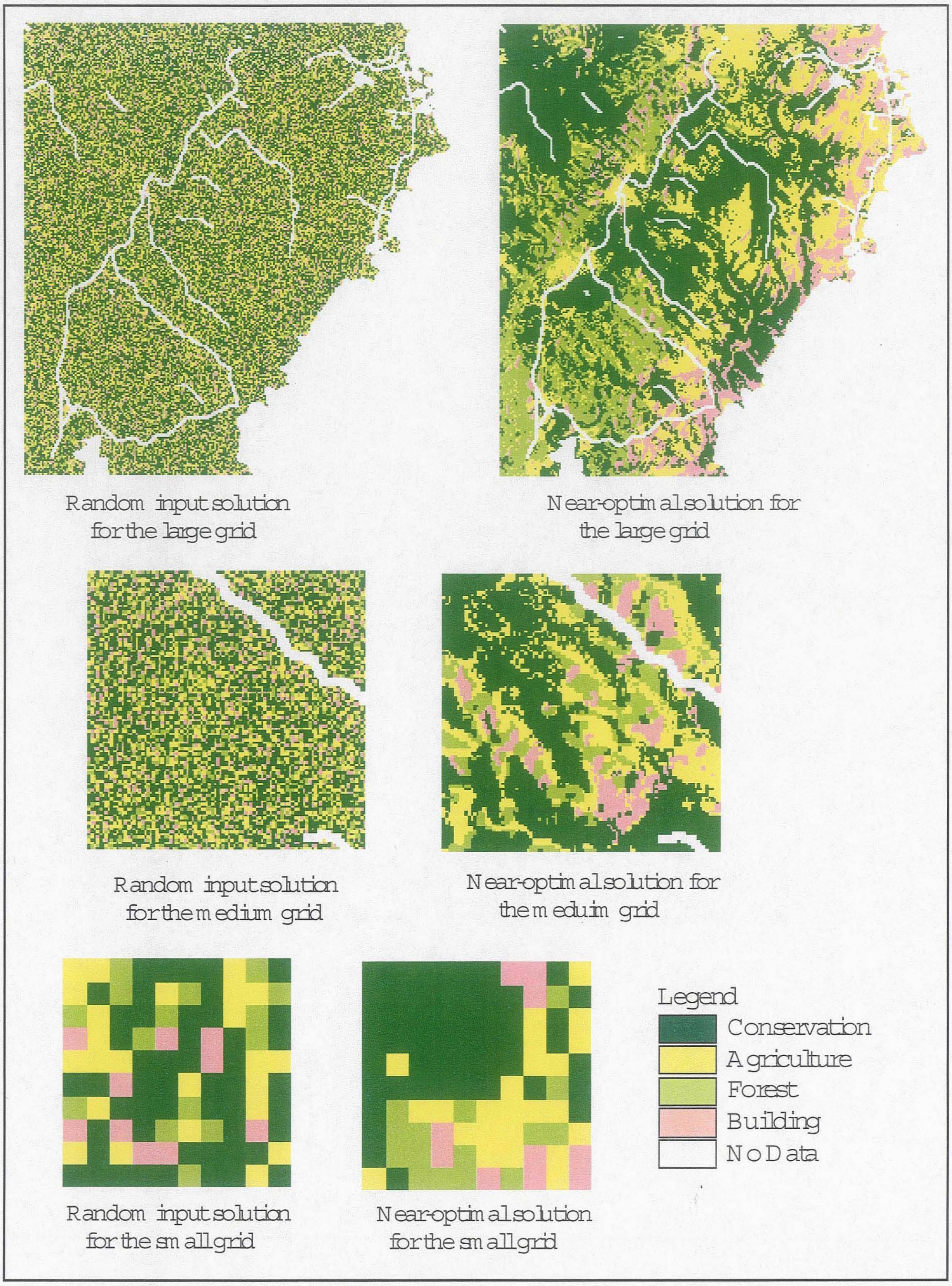


Figure 7.8 Random input solutions and near-optimal land use allocation by Simulated Annealing for the large, medium and small grids using the ordinal cost model

7.1.5 Assessing the performance of simulated annealing in solving a MOLAA problem

7.1.5.1 Analysing the spatial compactness without using the compactness function

The number of patches with corresponding cost functions is presented in Table 7.11 for the random initial input solution of the large grid of all cost models. The total number of patches under the eight-neighbours rule generally decreased with an improvement in the cost function in all cost models. For a small difference in the cost function, the number of patches might be higher even at the lower cost function. The solutions even with the same cost function might not have the spatial compactness and spatial pattern in the land use allocation. The spatial compactness was highest in the fuzzy cost model followed by the continuous model. The ordinal cost model gave the lowest spatial compactness in all three cost models.

Table 7.11 Number of patches (N_P) at for the random initial input solution of large grids

Total cost function for ordinal model = 68283000+
Total cost function for continuous model = 129703000+
Total cost function for fuzzy model = 451321000+

No of swaps per step	Ordinal model		Continuous model		Fuzzy model	
	C_F	N_P	C_F	N_P	C_F	N_P
186118	109348	6183	219566	5875	1112483	5267
1861180	5135	4262	17277	3608	33179	3230
9305900	3327	4105	4818	3471	964	3127
18611800	3001	4137	1822	3453	117	3124

Note: The spatial compactness was found to be more enhanced in the fuzzy model than in the continuous and ordinal models in the large grid MOLAA problem.

In the medium grid MOLAA problem, the spatial compactness was found to be inconsistent among the three cost models (ordinal, continuous and fuzzy). When the spatial compactness was analysed for two medium grids obtained from the large grid, the algorithm produced a more spatially compact allocation in the continuous model in one grid and in the fuzzy model in another grid. The land use allocation was even more spatially compact in the ordinal model than in the continuous model in the latter grid.

7.1.5.2 Computation time

Figure 7.9 illustrates computation time at a very slow cooling rate with four different swapping rates (S_R) = ($1*V_c$), ($10*V_c$), ($50*V_c$) and ($100*V_c$) in the medium grid using the greatest difference initial input solution for all cost models. The computation time increased with the higher swapping rates and cooling rates for all cost models. However, the algorithm terminated earliest in the ordinal cost model and took the longest time to deliver a solution in the continuous cost model. The computation time increased from the very fast to the very slow cooing rates for the same swapping rate with the higher number of control parameter steps.

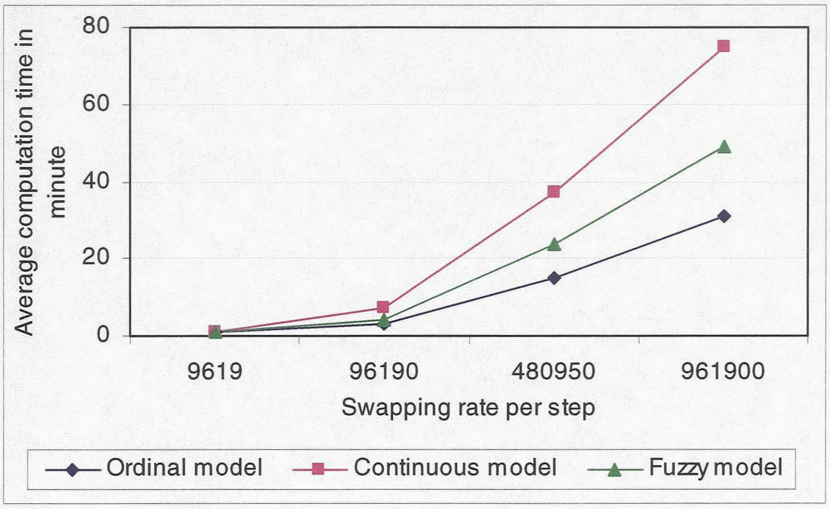


Figure 7.9 Average computation time at very slow cooling rate and four swapping rates for all three cost models in the medium grid

The run time markedly increased with the increase in the grid size under the influence of swapping rates and cooling rates. The run times for the large grid of all cost models for the random input model are given in the Table 7.12. Among the cost models, the ordinal cost model had the lowest run time. Except in a few annealing schedules, the fuzzy cost model had the highest run time.

Table 7.12 Run time for the random initial input solution of the large grid size for all cost models

Swaps per step	Very fast cooling rate (0.2)			Fast cooling rate (0.5)		
	Ordinal	Continuous	Fuzzy	Ordinal	Continuous	Fuzzy
186118	0:02	0:02	0:02	0:04	0:03	0:04
1861180	0:16	0:16	0:17	0:25	0:38	0:38
9305900	1:08	1:21	1:22	0:56	2:46	2:21
18611800	1:46	2:43	2:45	1:59	3:20	3:11
Swaps per step	Very fast cooling rate (0.8)			Fast cooling rate (0.98)		
	Ordinal	Continuous	Fuzzy	Ordinal	Continuous	Fuzzy
186118	0:11	0:13	0:14	0:13	0:18	0:22
1861180	0:37	0:48	0:57	2:06	2:12	2:28
9305900	1:57	2:17	2:30	10:10	10:14	11:09
18611800	2:49	3:26	5:13	20:24	20:28	23:25

7.1.6 Appropriate annealing schedule for Simulated Annealing in solving a MOLAA problem

An appropriate annealing schedule is a combination of all annealing parameters at which the algorithm minimizes the cost function close to optimum or near optimum cost function within a reasonable time. The algorithm delivered an optimum solution with annealing schedule (C_R, T_1, S_R) = (0.2, low, 100*V_C) for a small grid (10 by 10 cells) size problem in less than a minute in a Pentium IV PC. For the medium grid (100 by 100 cells) size problem, the same PC took less than three to four hours for improving the cost function to near optimum in continuous cost model (see Table 7.9). However, the algorithm could deliver a close solution to the near-optimal solution in much less computation time. Hence, eight combinations of the annealing schedule using two swapping rates (S_R) = (50*V_C) and (100*V_C), two cooling rates (C_R) = (0.2) and (0.98) at the high (H) and low (L) values of initial control parameter were applied to the random initial input solution of the ordinal model in the medium grid MOLAA problem. Table 7.13 presents a comparison of the solutions for the average cost function and spatial compactness and the computation time taken by the algorithm with that of near optimum cost functions at the annealing schedule (C_R, T_1, S_R) = (0.98, high, 300*V_C) for the random and greatest difference initial input solution of the ordinal cost model.

The algorithm with (C_R, T_1, S_R) = (0.98, high, 100*V_C) produced a solution very close to the near-optimal solution. The algorithm with the annealing schedule (C_R, T_1, S_R) = (0.2, high, 100*V_C) produced a better solution than the annealing schedules (C_R, T_1, S_R) = (0.2, low, 50*V_C), (0.2, high, 50*V_C) and (0.2, low, 100*V_C) but produced slightly less improvement in the cost function than the annealing schedule (C_R, T_1, S_R) = (0.98, high, 100*V_C). However, the computation time was about one minute for the annealing schedule (C_R, T_1, S_R) = (0.2, high, 100*V_C) and more than an hour for the annealing schedule (C_R, T_1, S_R) = (0.98, high, 100*V_C). Compromising the slight increase in the cost function, the annealing schedule (C_R, T_1, S_R) = (0.2, high, 100*V_C) was found to be appropriate in solving a MOLAA problem in the medium grid.

Table 7.13 Comparing cost function, spatial compactness and run time at different annealing schedules in the random initial input solution of the ordinal cost model for the medium grid

Total cost function = 4153000+

Annealing Schedule			Cost function			Spatial compactness		Run Time h:m	
T_1	C_R	S_R	Average	Change	% Change	Average	Change	Average	Saving
L	0.2	50*V_C	825	+116	0.00279	396	+44	0:01	1:33
L	0.2	100*V_C	869	+160	0.00385	364	+12	0:01	1:33
H	0.2	50*V_C	898	+189	0.00455	365	+13	0:02	1:32
H	0.2	100*V_C	804	+95	0.00229	364	+12	0:01	1:33
L	0.98	50*V_C	753	+44	0.00106	367	+15	0:19	1:15
L	0.98	100*V_C	733	+24	0.00058	363	+11	0:25	1:09
H	0.98	50*V_C	757	+48	0.00115	354	+2	0:31	1:03
H	0.98	100*V_C	730	+21	0.00051	366	+14	1:02	0:32

In the case of a large grid, the algorithm took more than 60 hours to generate the near-optimal solution with the annealing schedule (C_R, T_1, S_R) = (0.98, high, 300*V_C) (see Section 7.1.4). In order to find an appropriate annealing schedule for the large grid, the same four annealing schedules (used in the medium grid) were applied and compared with the near-optimal solution for the random initial input solution of the ordinal cost model. Table 7.14 presents a comparison of the differences in the cost function, run time and compactness between these annealing schedules and the near-optimal solution.

The cost function was much improved at the annealing schedule (C_R, T_1, S_R) = (0.98, high, 100*V_C) and delivered the solution in more than 20 hours computation time. The annealing schedule with the very fast cooling rate (C_R) = (0.2) was found to be very efficient at both swapping rates and initial control parameters. The annealing schedule (C_R, T_1, S_R) = (0.2, high, 100*V_C) produced the lowest mean cost function with the least variance compared to other annealing schedules solutions (C_R, T_1, S_R) = (0.2, low, 50*V_C), (0.2, high, 50*V_C) and (0.2, low, 100*V_C). Compromising between the cost function and the computation time, the algorithm with annealing schedule (C_R, T_1, S_R) = (0.2, high, 100*V_C) was found appropriate in solving a large grid MOLAA problem.

Table 7.14 Comparing cost function, spatial compactness and run time at different annealing schedules in the random initial input solution of the ordinal cost model for the large grid

Total cost function = 68283000+

Annealing Schedule			Cost function			Spatial compactness		Run Time *h:m*	
T_1	C_R	S_R	Average	Change	% Change	Average	Change	Average	Saving
L	0.2	$50*V_C$	3347	+2900	0.00424	4133	+28	1:09	61:06
L	0.2	$100*V_C$	3118	+2671	0.00391	4166	+61	1:24	60:51
H	0.2	$50*V_C$	3235	+2788	0.00408	4150	+45	1:10	61:05
H	0.2	$100*V_C$	2990	+2543	0.00372	4146	+41	1:37	60:38
L	0.98	$50*V_C$	1092	+645	0.00094	4126	+21	7:00	55:15
L	0.98	$100*V_C$	764	+317	0.00046	4092	-13	14:12	48:03
H	0.98	$50*V_C$	1062	+615	0.00090	4106	+1	10:12	52:03
H	0.98	$100*V_C$	762	+315	0.00046	4096	-9	20:26	41:49

7.1.7 Applying compactness function in solving a MOLAA problem

In order to apply the compactness function in the algorithm, compactness factors (F_C) = (25, 50, 100 and 200) were applied using the appropriate annealing schedule with (C_R, T_1, S_R) = (0.2, high, $100*V_C$). Figure 7.10 displays the improvement in the spatial compactness using these compactness factors in the ordinal data type model (random input) of the medium grid. The cost function, run time and spatial compactness in terms of number of patches in the eight-neighbours rule is shown in Tables 7.15 and 7.16 for medium and large grids using random and greatest difference initial input solutions of ordinal cost model.

Table 7.15 Spatial compactness after applying compactness function at appropriate annealing schedule in the medium grid of ordinal cost model

Total cost function = 4153000+

Compactness Factor	Random input			Greatest difference input		
	Cost function	Run time *h:m*	No. of patches	Cost function	Run time *h:m*	No. of patches
0	863	0:01	372	512	0;01	386
25	62072	0:06	65	63344	0:04	74
50	126174	0:08	52	124254	0:04	50
100	199508	0:07	39	202789	0:09	43
200	251647	0:10	38	275162	0:10	27

Note: The spatial compactness was enhanced by using the higher value of compactness function in the algorithm for the medium grid.

Table 7.16 Spatial compactness after applying compactness function at appropriate annealing schedule in the large grid of ordinal cost model

Total cost function = 68283000+

Compactness Factor	Random input			Greatest difference input		
	Cost function	Run time *h:m*	No. of patches	Cost function	Run time *h:m*	No. of patches
0	3001	1:46	4137	2822	1:55	4152
25	1284085	4:11	659	1277985	4:11	651
50	2115753	4:12	495	2134094	4:11	468
100	3075799	4:12	392	3097252	4:11	399
200	4519682	4:12	360	4166573	4:09	348

Note: The spatial compactness was enhanced by using the higher value of compactness function in the algorithm for the large grid.

The improvement in the spatial compactness in the continuous and fuzzy cost models are given in Annex 4 for the medium and large grid using these values of compactness factors. The spatial compactness (with lower value of the number of patches) improved with the higher values of compactness factor from 25 to 200 for the medium grid. The degree of improvement in spatial compactness is largely controlled by the compactness factor values and the range of the cost values in the cost models. These compactness factor values were found to be the most appropriate for the ordinal cost model with the lowest range of cost values. The fuzzy cost model had the largest range of cost values, therefore, these compactness factors did not improve the spatial compactness more in the fuzzy model than in the ordinal and continuous models.

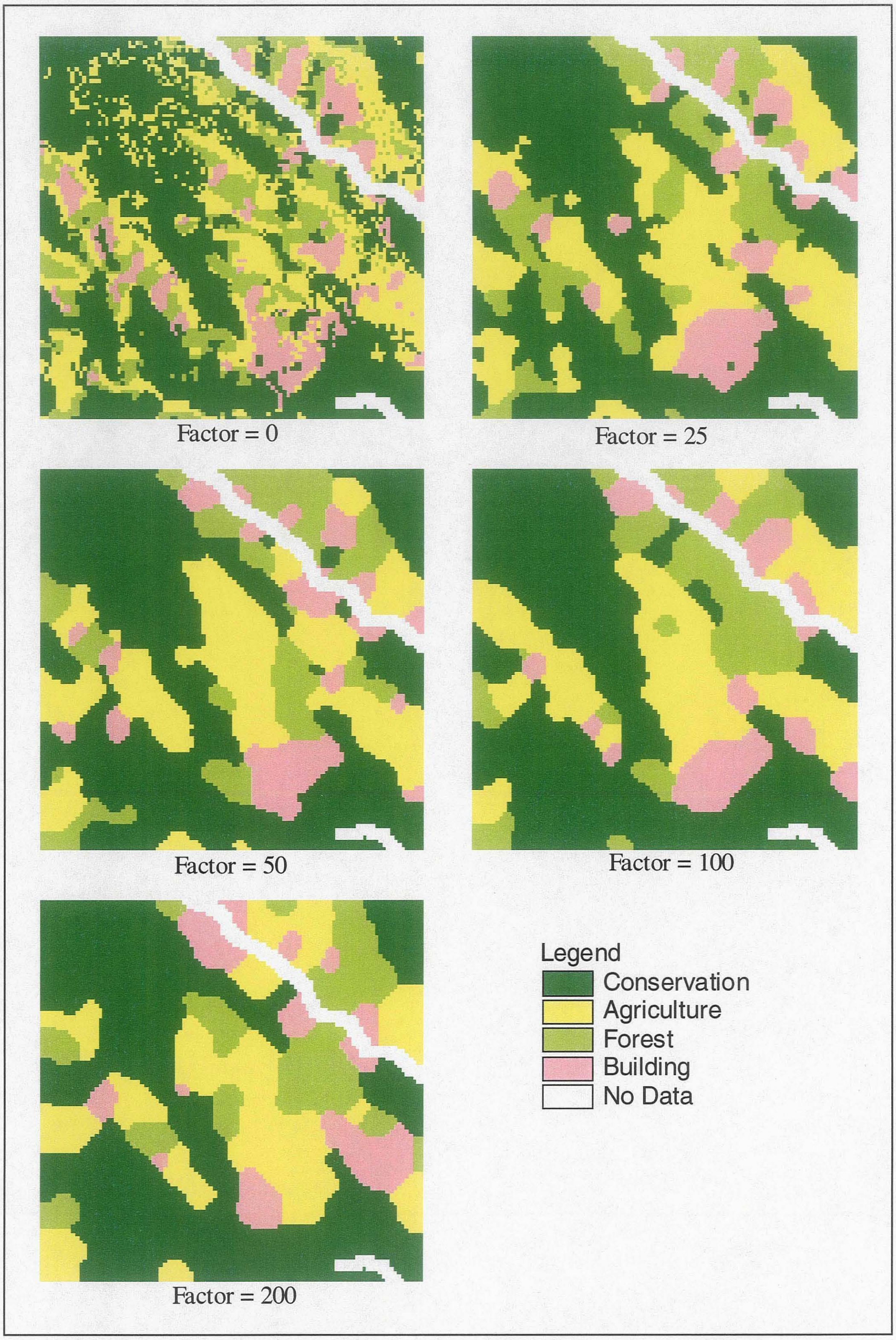


Figure 7.10 Improvement in the spatial compactness applying different compactness factors to the ordinal model for the medium grid MOLAA problem

7.1.8 Appropriate initial input solution and cost model in solving the MOLAA problem

Table 7.17 presents the average cost functions, run time and spatial compactness by applying Simulated Annealing, using the appropriate annealing schedule (C_R, T_1, S_R)= (0.2, high, 100*V_c) to the medium and large grid MOLAA problem. The improvement in the cost function measured as compared to the initial cost function for the random initial input solution was found to be the highest for the fuzzy cost model in both grid sizes. In the medium grid, the minimization in the cost function was found better in the cheapest and the greatest difference initial input solutions than in the random initial input solution. The algorithm also performed better when using the random initial input solution than in the cheapest or greatest difference initial input solutions in the large grid. These results rejected the null hypothesis regarding the influence of the different initial input solution on cost function minimization.

The algorithm produced a more spatially compact land use allocation using the fuzzy model in the large grid. However, the spatial compactness was found to be inconsistent among the three models in the medium grid (see Section 7.1.5.1) The mean number of patches was found to be significantly different among the solutions by using the three cost models. Hence the null hypothesis regarding the influence of the cost model on the spatial compactness was rejected.

Table 7.17 Comparing the average cost functions, run time and spatial compactness for all initial input solutions and cost models in the medium and large grid MOLAA problem

Cost model	Initial Input solution	Medium Grid C_F	R_T *h:m*	N_P	Change in C_F%	Large Grid C_F	R_T *h:m*	N_P	Change in C_F%
Ordinal	Random	4153823	0:01	363	-21.498	68285985	1:54	4134	-26.987
	Cheapest	4153559	0:01	372	-21.503	68285794	1:42	4111	-26.988
	Greatest	4153534	0:01	361	-21.504	68285711	1:43	4140	-26.988
Continuous	Random	7512941	0:01	276	-16.218	129706140	2:43	3457	-21.896
	Cheapest	7512343	0:01	278	-16.225	129706543	2:43	3450	-21.895
	Greatest	7512321	0:01	277	-16.226	129706609	2:43	3453	-21.895
Fuzzy	Random	29615870	0:02	295	-27.492	451320049	2:41	3124	-36.451
	Cheapest	29612391	0:02	293	-27.501	451320552	2:38	3123	-36.451
	Greatest	29612421	0:02	296	-27.501	451320263	2:41	3124	-36.451

7.2 Discussion

This part of the research applied Simulated Annealing with three different cooling functions in the annealing schedule. The reduction of the initial control parameter by a specified constant factor at every control parameter or cooling step (Mode 1) performed better than the other two cooling functions (see section 7.1.2). In Mode 1, the acceptance of hot-swaps allows the system to escape from being trapped in the local minimum at the expense of increasing the cost function, whereas the stopping rule (cold-swap = 0) allows enough cold-swaps to improve the cost function to its minimum. The best performance of this cooling function over others can be attributed to the number of possible cold-swaps to minimize the cost function increased by the hot-swaps. In Modes 2 and 3, the algorithms accepted moves with increased cost functions and terminated after attaining the prescribed number of control parameter steps (N_{CS}) while the cost minimization was in progress. It means that the algorithm stops before the cost function culminates at its minimum.

Mode 1 was also found to be easy to understand and relatively simple to implement in an annealing schedule. Only the initial control parameter (T_I) and the cooling rate (C_R) need to be specified. In other modes, the annealing schedule requires defining the final value of the control parameter and the number of control parameter steps (N_{CS}) in addition to the initial control parameter. In the case of Mode 1, the algorithm always uses final control parameter (T_N) value as zero and does not require N_{CS} to be defined. The stopping rule for terminating the algorithm is also very simple and straightforward in this cooling function, as the algorithm will stop as soon as cold-swap becomes zero. In the case of Modes 2 and 3, the number of cooling steps (N_{CS}) and the final control parameter (T_N) determine the stopping time for the algorithm. However, I have not found any way of prescribing these parameters for an appropriate annealing schedule in these modes.

This research found a similar influence of three initial control parameters (T_I) on cost minimization to that described by van Laarhoven (1987). The annealing schedule with initial control parameters (T_I) = (50, 80 and 98 percent of hot-swap acceptance in the first cooling step) had the same influence on the cost function minimization at the same cooling rate and the swapping rate. Johnson *et al.* (1991) also found that the higher number of hot-swap acceptance at the high value of initial control parameter does not contribute significantly to improving the cost function in the final solution. However, the values of initial control parameter are determined by the range and magnitude of the values in the cost models. The distribution of values in the initial input solutions like random, cheapest and greatest difference models also affects the values of initial control parameter based on the hot-swap acceptance percentage of in the initial step (see Section 7.1.1).

The cooling rate was found to be an important annealing parameter in the annealing schedule. The cooling rate controls the cost minimization through reducing the initial control parameter and also determining the number of cooling steps. At the very fast cooling rate (C_R) = (0.2), the initial control parameter reduced by 80 percent in every step and the algorithm reached the stopping criterion in a few cooling steps (fewer than 70 steps). However, in the case of the very slow cooling rate (C_R) = (0.98), the initial control parameter reduced at the rate of two percent in every step and allowed more than 450 control parameter steps before getting to the stopping criterion.

In a MOLAA problem, the very fast cooling rate performed more efficiently than the very slow cooling rate at the higher value of swapping rate (S_R) = ($100 * V_c$). The very fast cooling rate reduced the initial control parameter very quickly and sharply decreased the number of hot-swaps acceptances in the second control parameter step. However, the high swapping rate enabled the algorithm with the very fast cooing rate to search for all spaces and minimized the cost function satisfactorily, even in a small number of control parameter steps. In contrast, at the very slow cooing rate, the initial control parameter decreased very slowly, allowing a large number of hot-swap acceptances for several cooing steps. While the algorithm at the very slow cooling rate took more than 450 control parameter steps with huge number of acceptances of the hot-swaps and cold-swaps, the cost function did not improve much because of the cost minimization achieved by the cold-swaps was offset by the acceptance of the hot-swap.

The choice of swapping rate (S_R) is the key to the Simulated Annealing as it mainly determines the improvement in the cost function along with the cooling rate (C_R). In the physical annealing process, the configuration should reach thermal equilibrium for each temperature step, otherwise the solids would not get into the ground state (van Laarhoven and Aarts, 1987). For a combinatorial problem, Sundermann (1995) suggested using a number of iterations at which the cost function does not get changed.

However, the appropriate swapping rate in solving a real land use allocation problem has not been suggested. A higher number of iterations generally improves the cost function (McDonnell *et al.*, 2002). However, this study found that the rate of improvement in the cost function decreased with the higher the number of swaps, and after a certain number of iterations (swapping rate), the algorithm did not improve the cost function significantly. Nevertheless, the higher number of swaps increases the computation time. With a higher swapping rate like (S_R)= ($100*V_c$) together with the very slow cooling rate (C_R,) = (0.98), the computation time increased markedly depending upon the size of the problem.

The algorithm successfully solved a MOLAA problem through applying the initial input models based on the ordinal, continuous and fuzzy cost models. The solutions by the algorithm to different cost models were not comparable in terms of the cost function minimization, having a different range, magnitude and distribution of the cost suitability values in these cost models. However, the cost model of the initial solution certainly affected the spatial pattern of the final solution due to inherent differences in representing the suitability of a land unit to a land use among these cost models. It was found that the spatial compactness was more improved in the fuzzy cost model for the large grid. The higher number of discrete values representing the land use suitability in the fuzzy model, the more spatially compact the land use allocations produced by the algorithm. The ordinal model had the least discrete values for representing the land use suitability and therefore the spatial compactness was not improved in this cost model compared to the continuous and fuzzy cost models for the large grid.

The algorithm minimizes the cost function to its minimum in all initial input solutions of all cost models as determined by the annealing schedule. Although the random initial input solution has the highest value of initial cost function with massively scattered land use allocation (the highest number of patches), the algorithm produces a solution very close to the cheapest and greatest difference initial input solutions in terms of the cost function and spatial compactness for the same cost model. The total number of patches reduced and enhanced the spatial compactness, as the optimisation progressed minimizing the initial cost function by allocating the land use with the lowest suitability value for each land unit. However, the same cost functions could not produce the same spatial compactness because of more than one land unit having the same cost value for a land use. The allocation of a land use to a land unit with the same cost value could not affect the cost function, but the location of the selected land unit could affect the spatial compactness. Even the higher cost function often produced more spatially compact land use allocation by allocating the same land use to the adjoining land units with the higher suitability value. This was seen in the small grid problem where the algorithm generated an optimum solution with the minimum cost function but decreased the spatial compactness by using the greatest difference initial input solution (see section 7.1.4).

Applying the compactness function in the algorithm, the higher factor (reward) value enhances the spatial compactness by reducing the total number of patches. An increase in the cost function occurred because of allocating adjacent land units having the same land uses, despite their higher costs. Among the different cost models with different ranges and magnitudes of cost values, the same compactness factor did not produce the same level of compactness. The decision maker and stakeholder may apply different compactness factors to arrive at a satisfactory compromise of the cost function and spatial compactness in a MOLAA problem.

7.3 Conclusion

The Simulated Annealing algorithm was applied to solving a MOLAA problem. An appropriate annealing schedule and input requirement were also searched for the algorithm. By applying this algorithm to three different grid sizes (small, medium and large) MOLAA problems at different cooling functions, swapping rates, initial input solutions and cost models, this study has drawn the following conclusions.

1. Among the three cooling functions used in the Simulated Annealing, the cooling function in Mode 1 produced the highest improvement in the cost function in all annealing schedules. Besides the superior cost function, the annealing schedule based on Mode 1 was found to be simple to understand and easy to implement. Therefore, this cooling function was chosen for investigating an appropriate number of swaps (S_R) and the initial control parameter (T_1) for a MOLAA problem.

2. The study evaluated the influence of the three values of initial control parameters as determined by 50, 80 and 98 percent acceptance of hot-swaps at the first cooling step for cost function minimization. For the same value of cooling rates and swapping rates, the different values of initial control parameter did not

produce any significant difference in the cost function minimization. This implies that the higher value of initial control parameter is not necessary for improving the cost function in solving a MOLAA problem, as in the metal crystallization by the analogous annealing process.

3. Among the four cooling rates (C_R) = (0.2, 0.5, 0.8 and 0.98), the very slow cooling rate (C_R) = (0.98) produced the highest improvement in the (mean) cost function by cooling at the rate of two percent per step of the initial control parameter. Although the very fast cooling rate (C_R) = (0.2) produced the smallest improvement in the cost function by cooling the initial control parameter at the rate of 80 percent every step, the algorithm was more efficient in terms of the computation time at a very fast cooling rate producing a slightly higher cost function than the very slow cooling rate.

4. The swapping rate exerted the greatest influence on improving the cost function of all the annealing parameters in the Simulated Annealing algorithm. Among the four swapping rates (S_R) = ($1*V_C$, $10*V_C$, $50*V_C$ and $100*V_C$), the higher swapping rate (S_R) = ($>50*V_C$) produced the maximum improvement in the cost function in a MOLAA problem. At the higher number of swaps (S_R) = ($>50*V_C$), the algorithm searched the maximum combination of the decision variables (land uses and land units) in order to improve the cost function whereas the lower swapping rates (S_R) = ($<50*V_C$) might not be adequate to search for all the land units and therefore, the algorithm was terminated even at the higher cost function.

5. For the medium grid MOLAA problem, the cheapest or greatest difference initial input solution was found to be more appropriate than the random input solution. However, in the case of the large grid, the algorithm improved cost function more by using the random initial solution in the continuous and fuzzy models.

6. The algorithm produced an optimum solution for the small grid with the annealing schedule (C_R, T_I, S_R) = (0.2, high, $100*V_C$) using the greatest difference initial input solution. For the medium and large grid MOLAA problems, the algorithm with the annealing schedule (C_R, T_I, S_R) = (0.98, high, $300*V_C$) delivered a solution with a near-optimum cost function. However, the swapping rate (S_R) =

($300*V_C$) markedly increased the computation time to more than 60 hours for generating the near-optimum solution for the large grid MOLAA problem.

7. The highest spatial compactness was found in the fuzzy model followed by the continuous model, in the large grid MOLAA problem. However, the land use allocation was more compact in the continuous model than in the fuzzy model in the medium grid MOLAA problem. The spatial distribution and the variability (number) in the cost values in the input cost suitability model produced a different measure of spatial compactness in these models.

8. It was also found that the computation time increased with the higher swapping rate and cooling rates in the annealing schedule. The run time markedly increased from the medium grid to the large grid size MOLAA problem. Among the three cost suitability models, the algorithm required the longest run time for delivering a solution in the fuzzy models for both grid sizes.

9. By assessing the performance of the Simulated Annealing in terms of the quality of the solution (cost function and spatial compactness) and the run time, an appropriate annealing schedule with (C_R, T_1, S_R) = (0.2, high, $100*V_C$) was found appropriate for applying the Simulated Annealing to medium and large grid MOLAA problems. The run time was reduced to about one minute in this annealing schedule, from about two hours for generating a near-optimal solution in the medium grid using the appropriate annealing schedule. In the large grid MOLAA problem, the appropriate annealing schedule (C_R, T_1, S_R) = (0.2, high, $100*V_C$) produced a cost function close to a near-optimal solution much more efficiently than the annealing schedule (C_R, T_1, S_R) = (0.98, high, $100*V_C$) with slightly higher the cost function than in the latter annealing schedule.

10. Among the three models, the highest improvement in the cost function was found in the fuzzy models, brought about by reducing the cost function by about 27 percent less than the initial cost in the random input solution in the medium grid MOLAA problem. In the large grid MOLAA problem, the algorithm improved the cost function by about 36 percent less than the initial cost in the random input solution in the fuzzy model. The solution was found to be about 25 percent more spatially compact in the fuzzy model than in the ordinal model in the large grid.

Although the same annealing schedule (C_R, T_1, S_R) = (0.2, high, 100*V_C) delivered a solution about an hour quicker in the ordinal model than in the fuzzy model, the quality of the solution in terms of improvement in the cost function and the spatial compactness in the latter model were better than in the former model. Unlike in the medium grid, the algorithm produced a slightly better solution using the random input solution than in the cheapest or greatest difference input solution. Hence, the random initial solution of a fuzzy model was found appropriate in solving a MOLAA problem applying Simulated Annealing.

11. In general, higher values of the compactness factor better enhanced the spatial compactness and the value should be determined from the data range and values in the input cost suitability models.

7.4 Summary

A detailed application of the Simulated Annealing algorithm in solving a MOLAA problem was illustrated by applying the algorithm to the hypothetical MOLAA problem. The MOLAA problem was formulated as a combinatorial optimisation problem and subjected to optimisation through cost function minimization. A summary of the findings in relation to the influence of the different parameters, cost model and initial input solution is given in Table 7.18.

The algorithm with (C_R, T_1, S_R)= (0.2, low, 100*V_C) can produce a global solution to the small grid (10 by 10 cells) MOLAA problem. In the case of the medium and large grids, the algorithm with appropriate annealing schedule (C_R, T_1, S_R)= (0.2, high, 100*V_C) could deliver a solution close to the near-optimal solution in a very quick time. The algorithm performed better using fuzzy cost model and the random initial input solution in the large grid whereas in the medium grid, the cheapest and greatest difference initial solution gave better result.

Chapter 8, the next chapter, will present the results of applying Tabu Search to the same hypothetical MOLAA problem. In Chapter 9, the MOLA module, Simulated Annealing and Tabu Search will be compared to assess their performance in solving a MOLAA problem.

Table 7.18 A summary of the parameters, their descriptions and hypothesis

Parameters	Comment on null Hypothesis	Findings
Cooling Function	Rejected	The algorithm with the cooling function Mode 1 cooled the initial control parameter until the cold-swaps became zero and thus, this mode produced better improvement in the cost functions than Modes 2 and 3.
Initial Control Parameter	Accepted	Although there was different in acceptance of hot-swaps at three values of initial control parameter, the improvement in the cost function was not significantly affected using the low, medium and high values of initial control parameter.
Cooling rate	Rejected	With the slower cooling rate, the number of iteration steps and computation time increased. Hence, the minimization of cost function was significantly different between the very fast and very slow cooling rates.
Swapping rate	Rejected	The swapping rate influenced the cost minimization by determining the number of cold-swaps and hot-swaps. At the higher swapping rates (S_R)= (=>100*V_C), the algorithm produced more improvement in the cost function than at the lower swapping rates (S_R) = (=>50*V_C).
Compactness function	Rejected	The compactness factor allowed acceptance of move that increased the spatial compactness depending upon the cost model. The higher values of compactness factor produced better spatial compactness in all cost models.
Initial input solution	Rejected	The algorithm produced more improvement in the cost function in the cheapest and greatest difference initial input model in the medium grid whereas in the large grid, the random input model had the highest improvement in the cost function.
Cost model	Rejected	The algorithm produced more spatial compact land use allocation using fuzzy cost model than in other models in the large grid.

Chapter 8

RESULTS AND DISCUSSION III – APPLYING TABU SEARCH TO THE HYPOTHETICAL MOLAA PROBLEM

This chapter presents the results of applying the Tabu Search algorithm explained in Chapter 3 to the hypothetical MOLAA problem. The algorithm was applied in static and dynamic search strategies, three neighbourhood sizes, four Tabu lengths and four swapping rates. The performance of the algorithm in solving a MOLAA problem was assessed by improvement in the cost function, run time and spatial compactness. Table 8.1 presents a summary of these parameters, their brief description and null hypothesis addressing their influence on the cost function or spatial compactness.

Table 8.1 A summary of the parameters, their descriptions and hypothesis

Parameters	Brief description	Null Hypothesis
Search Strategy	Static and dynamic modes – it determines the swapping rates per iteration step.	The minimization of the cost function does not differ significantly between static and dynamic search modes.
Neighbourhood size	Randomly selected 1, 4 and 8 neighbours – it affects the selection of the best land unit for swapping.	The improvement in the cost function does not differ significantly among different values of neighbourhood size.
Tabu length	Specifies the size of Tabu list - it affects the algorithm by restricting swapping of land use in the previous moves.	The minimization of the cost function does not differ significantly among the Tabu lengths.
Swapping rate	Total number of land use exchange allowed between two land units in each step - it affects the cost minimization by controlling the number of cold-swaps and hot-swaps.	The minimization of the cost function does not differ significantly among the swapping rates.
Compactness function	A function that takes into account of the spatial compactness at every swapping - it affects the compactness by rewarding a move that increases the spatial compactness.	The spatial compactness does not differ significantly among the different values of compactness factor.
Initial input solution	Initial solutions generated by random, cheapest and greatest difference methods – the initial solution may influence the output and performance of the algorithm.	The minimization of the cost function does not differ significantly among three initial input solutions.
Cost models	Suitability models derived from the criteria maps using ordinal, continuous and fuzzy-WLC methods - the models may influence on the output and performance of the algorithm.	The spatial compactness does not differ significantly among three cost models.

8.1 Results

8.1.1 Influence of static and dynamic modes on cost function minimization

Tabu Search was applied in static and dynamic modes (discussed in Chapter 5) to the MOLAA problem in the medium grid MOLAA problem. Table 8.2 presents the mean cost functions at four Tabu lengths (T_L) and four swapping rates (S_R) in the both the modes. Four Tabu lengths (T_L) = (962, 1443, 1924 and 2405) were used, as determined by the 10, 15, 20 and 25 percents of valid cells (9619) in the medium grid. The mean cost function was found to be lower in the dynamic mode than in the static mode for 13 out of 16 parameter settings. However, these differences in the mean cost function were not found significant by the t-test with two-sample assuming unequal variance at 95 percent confidence interval. Hence, the null hypothesis regarding the search strategy was accepted, as there was no significant difference in minimization of the cost function between these two modes.

Table 8.2 Mean cost function and mean difference by Tabu Search in static and dynamic modes for medium grid (random input model) of ordinal cost model

Mean cost function (C_F) = 4153000+

No of swaps per step	Cost function at Tabu length = 962			Cost function at Tabu length = 1443		
	Static Mode	Dynamic Mode	Mean Difference	Static Mode	Dynamic Mode	Mean Difference
9619	2377	1876	501	2385	1851	534
96190	967	956	11	1093	938	155
480950	854	830	24	871	816	55
961900	816	805	11	800	805	5
No of swaps per step	**Cost function at Tabu length = 1924**			**Cost function at Tabu length = 2405**		
	Static Mode	Dynamic Mode	Mean Difference	Static Mode	Dynamic Mode	Mean Difference
9619	2220	1872	348	2194	1979	215
96190	1093	934	159	1009	939	70
480950	815	820	- 5	849	819	30
961900	823	821	- 2	804	811	- 11

Note: The mean cost function did not differ significantly between the static and dynamic modes.

Although the mean cost functions were not significantly different between the static and dynamic modes, the computation time was found to be appreciably higher for the dynamic mode. Figure 8.1 illustrates the run time differences in the dynamic and static modes with Tabu lengths (T_L) = (1924 and 2405) at three swapping rates (S_R) = ($10*V_C$, $50*V_C$ and $100*V_C$). The time difference was found to be increased with the higher swapping rates and Tabu lengths. Based on the improvement in the cost function and run time, the algorithm in static mode was found to be more efficient than the dynamic mode. This result was also found valid in the large grid MOLAA problem. Hence, the algorithm in static mode was chosen for solving a MOLAA problem.

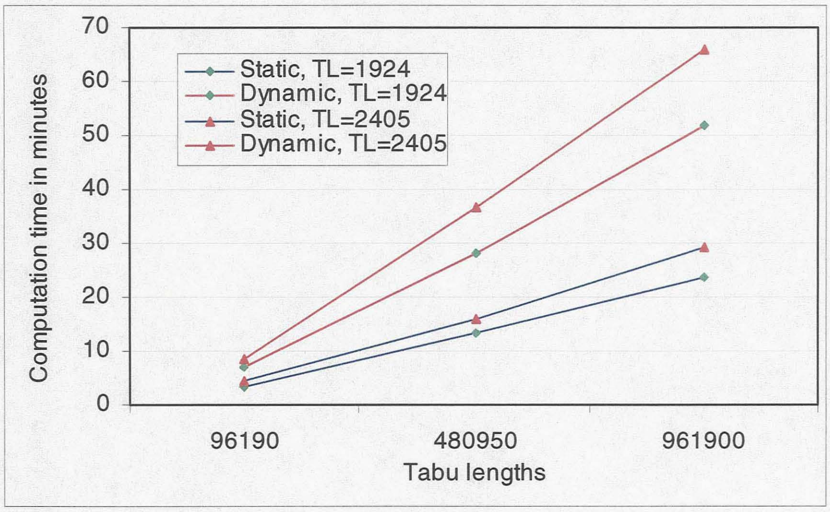


Figure 8.1 Run time for the static and dynamic modes at two Tabu lengths for the medium gird

8.1.2 Influence of neighbourhood sizes on cost function minimization

Three neighbourhood sizes (N_S) = (1, 4 and 8) were used in the Tabu Search algorithm in order to find an appropriate neighbourhood size for generating a new solution. The mean cost functions at these neighbourhood sizes are given in the Table 8.3 for four swapping rates (S_R) = ($1*V_C$, $10*V_C$, $50*V_C$ and $100*V_C$) and four Tabu lengths (T_L) = (962, 1443, 1924, and 2405). Among 16 combinations of Tabu length and swapping rates, the cost function generally improved with the higher values of neighbourhood sizes from one to eight. The t-test with two-sample assuming unequal variance found the mean cost functions at the neighbourhood size (N_S) = (1) were significantly different from the mean at the higher neighbourhood sizes for all the Tabu length at the swapping rates (S_R) = ($1*V_C$) and ($10*V_C$). However, the means were not found significantly different at the higher swapping rates (S_R) = (=>$50*V_C$) among all neighbourhood sizes. The null hypothesis about the influence of the neighbourhood sizes on the cost function was accepted only for the higher swapping rates (S_R) = (=>$50*V_C$). The statistical difference of the mean cost function at the neighbourhood size (N_S) = (1) is represented by the neighbourhood sizes in the superscript in the table.

Table 8.4 presents the cost difference and run time difference between the neighbourhood size (N_S) = (1) and the higher neighbourhood sizes (N_S) = (4 and 8). The cost differences were higher at the lowest swapping rates (S_R) = ($1*V_C$, $10*V_C$) and decreased with the increase in the swapping rates. However, the run time for delivering a solution by the algorithm increased with the higher values of neighbourhood sizes. Using the higher number of neighbourhood sizes (N_S) = (4 and 8) in the algorithm, an additional time was required for random selection of 4 or 8 cells and comparing the costs for selecting the cheapest cell to swap the land use. Therefore the neighbourhood size (N_S) = (1) was found more efficient than the higher neighbourhood sizes and it was chosen for further investigation. This finding rejected the of null hypothesis regarding the influenction of neighbourhood sizes on improvement in the cost function.

Table 8.3 Mean cost function at different neighbourhood size for medium grid (random input model) of ordinal cost model in static mode

Cost function (C_F) = 4153000+

No of swaps per step	Cost function at Tabu length = 962			Cost function at Tabu length = 1443		
	N_S = one	N_S = four	N_S = eight	N_S = one	N_S = four	N_S = eight
9619	$2425^{4,8}$	1292	1068	$2372^{4,8}$	1318	1061
96190	$1006^{4,8}$	845	831	$1016^{4,8}$	850	808
480950	846	817	796	859	802	805
961900	810	801	769	797	786	799
No of swaps per step	Cost function at Tabu length = 1924			Cost function at Tabu length = 2405		
	N_S = one	N_S = four	N_S = eight	N_S = one	N_S = four	N_S = eight
9619	$2088^{4,8}$	1516	1216	$2212^{4,8}$	1214	1112
96190	$1169^{4,8}$	898	918	$977^{4,8}$	838	836
480950	819	786	822	829	781	815
961900	827	794	787	801	788	796

Note: The mean cost function decreased with the increase in the neighbourhood size.

Table 8.4 Comparing the mean cost functions at neighbourhood (N_S) = (1) and the higher neighbourhood sizes for medium grid

No of swaps per-step	T_L = 962				T_L = 1443			
	(N_S = 1) – (N_S = 4)		(N_S = 1) – (N_S = 8)		(N_S = 1) – (N_S = 4)		(N_S = 1) – (N_S = 8)	
	C_F differnce	Time difference	C_F differnce	Time difference	C_F differnce	Time difference	C_F differnce	Time difference
9619	1133	<0:01	1357	0:01	1054	0:02	1311	0:05
96190	161	<0:01	175	0:01	166	0:03	208	0:07
480950	44	<0:01	50	0:01	81	0:05	78	0:07
961900	24	0:01	41	0:02	11	0:06	- 2	0:11
No of swaps per step	T_L = 1924				T_L = 2405			
	(N_S = 1) – (N_S = 4)		(N_S = 1) – (N_S = 8)		(N_S = 1) – (N_S = 4)		(N_S = 1) – (N_S = 8)	
	C_F differnce	Time difference	C_F differnce	Time difference	C_F differnce	Time difference	C_F differnce	Time difference
9619	572	0:09	872	0:25	998	0:19	1100	0:47
96190	271	0:14	251	0:32	139	0:28	141	1:06
80950	33	0:15	- 3	0:43	48	0:28	14	1:28
961900	33	0:23	40	0:50	13	1:22	5	1:42

Note: The computation time increased with the higher values of neighbourhood sizes.

8.1.3 Influence of Tabu length on cost function minimization

Eight Tabu lengths (T_L) as determined by 0.5, 1, 2.5, 5, 10, 15, 20 and 25 percentages of the valid cells (V_C) = (9619) in the medium grid were used in the algorithm in order to compare their influence on cost function minimization. Figure 8.2 displays the mean cost functions at Tabu lengths (T_L) = (48, 96, 241, 481, 962, 1443, 1924 and 2405) for four swapping rates (S_R) = ($1*V_C$, $10*V_C$, $50*V_C$ and $100*V_C$). The t-test with two-samples assuming unequal variances did not find a significant difference among these mean cost functions for the same parameter settings at 95 percent confidence interval. It means that the different values of Tabu length do not produce a significant difference in the cost function. Hence the null hypothesis about Tabu length was accepted.

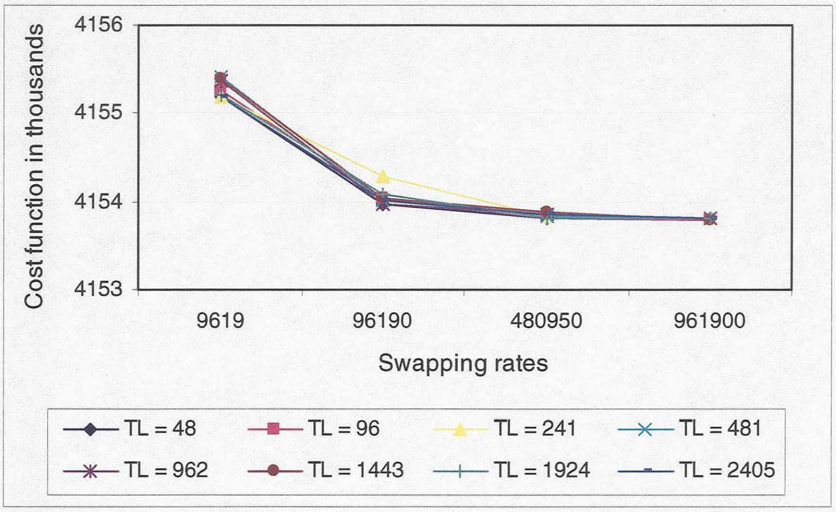


Figure 8.2 Mean cost functions at eight different Tabu lengths for medium grid (random input solution) of ordinal cost model in static mode

8.1.4 Influence of swapping rate on cost function minimization

Four swapping rates (S_R) = ($1*V_C$), ($10*V_C$), ($50*V_C$) and ($100*V_C$) as determined by multiples of one, ten, fifty and hundreds of the valid cells in the grid (V_C) per iteration step, respectively, were used in Tabu Search. The influences of these swapping rates were assessed by minimization of the cost function (Figure 8.3) in the static mode for the medium grid.

The lowest swapping rate (S_R) = ($1*V_C$) and the highest swapping rate (S_R) = ($100*V_C$) produced minimum and maximum improvements respectively, in the cost function for all Tabu lengths in the medium grid (random input solution) of the ordinal cost model. The mean cost functions of these solutions were found to be significantly different at 95 percent confidence interval by a statistical test. Hence, the null hypothesis was rejected. However, the algorithm at the higher swapping rates (S_R) = (>=50*V_C) produced solutions with no significant difference in their mean cost functions.

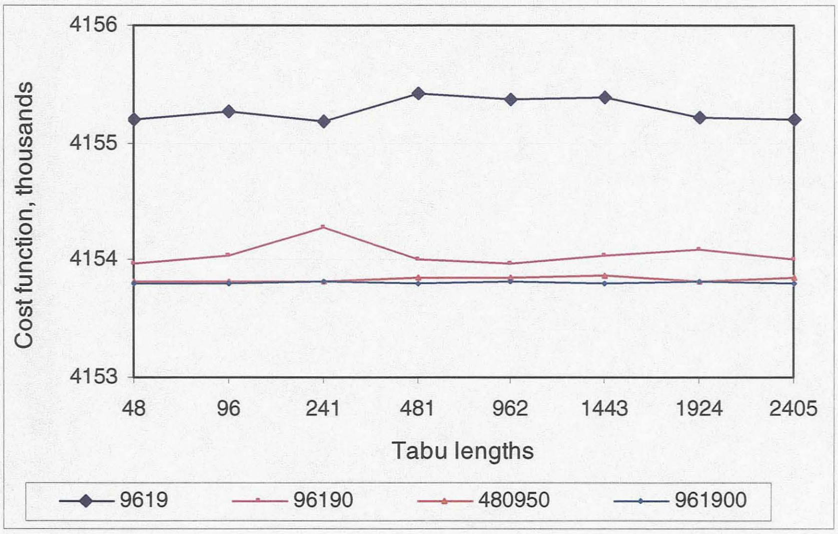


Figure 8.3 Mean cost function at different swapping rates for medium grid (random input model) of ordinal cost model in static mode

At the specified swapping rate, the number of cold-swap and hot-swap acceptances influenced the cost function minimization. Figures 8.4 and 8.5 show the accepted number of cold-swaps and hot-swaps at each step for four different swapping rates. The number of potential hot-swaps decreased at each step and became null at the 20th steps for the swapping rates (S_R) = (1*V_C, 10*V_C and 50*V_C) and at the 21st steps for (S_R) = (100*V_C). As long as the algorithm accepted the hot-swaps, the higher numbers of cold-swaps were accepted. The number of cold-swaps declined sharply after the hot-swaps became zero (Figure 8.5). The effects of both swaps on cost function minimization are shown in Figure 8.6. After the initial step, there was an increase in the cost function at the swapping rates (S_R) = (1*V_C, 50*V_C and 100*V_C) due to the acceptance of higher number of hot-swaps than the cold-swaps. At the swapping rate (S_R) = (1*V_C and 10*V_C), the cost function decreased markedly after there were no hot-swaps to reverse the cost minimization by the cold-swaps.

percent confidence interval by a statistical test. Hence, the null hypothesis was rejected. However, the algorithm at the higher swapping rates (S_R) = (>=50*V_C) produced solutions with no significant difference in their mean cost functions.

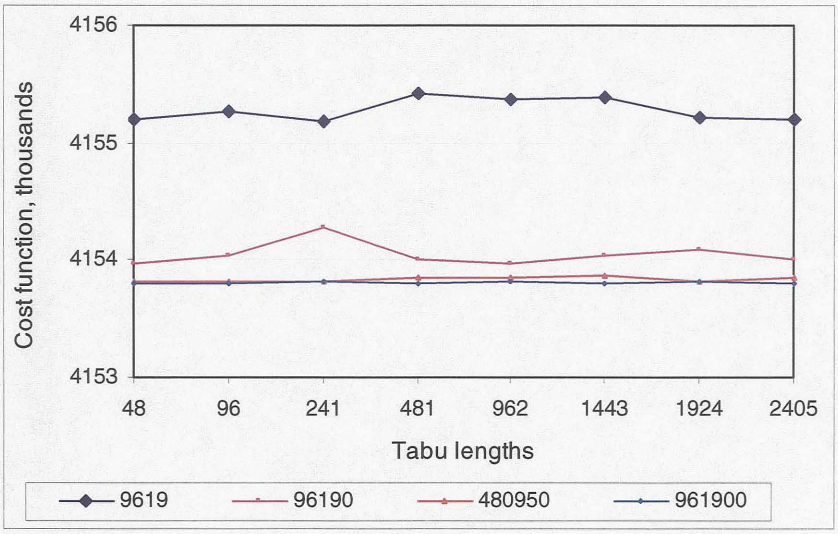


Figure 8.3 Mean cost function at different swapping rates for medium grid (random input model) of ordinal cost model in static mode

At the specified swapping rate, the number of cold-swap and hot-swap acceptances influenced the cost function minimization. Figures 8.4 and 8.5 show the accepted number of cold-swaps and hot-swaps at each step for four different swapping rates. The number of potential hot-swaps decreased at each step and became null at the 20th steps for the swapping rates (S_R) = (1*V_C, 10*V_C and 50*V_C) and at the 21st steps for (S_R) = (100*V_C). As long as the algorithm accepted the hot-swaps, the higher numbers of cold-swaps were accepted. The number of cold-swaps declined sharply after the hot-swaps became zero (Figure 8.5). The effects of both swaps on cost function minimization are shown in Figure 8.6. After the initial step, there was an increase in the cost function at the swapping rates (S_R) = (1*V_C, 50*V_C and 100*V_C) due to the acceptance of higher number of hot-swaps than the cold-swaps. At the swapping rate (S_R) = (1*V_C and 10*V_C), the cost function decreased markedly after there were no hot-swaps to reverse the cost minimization by the cold-swaps.

8.1.5 Optimum cost function for different grid sizes and cost models

Tabu Search was applied to the random and greatest difference input models to obtain near-optimal solutions for all grid sizes of the MOLAA problem. Tabu lengths did not influence the cost function minimization but the higher values of Tabu length increases the computation time for the algorithm (see section 8.1.3). Hence, the lowest value of Tabu lengths (T_L) = (10) was used for all grids. The higher swapping rate has the highest influence on the cost function minimization (see section 8.1.4). However, the algorithm with the swapping rate (S_R) = ($500*V_C$) did not improve the cost function more significantly than the swapping rate (S_R) = ($300*V_C$). Hence, the cost functions at the latter swapping rate were taken to be the closest to the optimum for the medium and large grid MOLAA problems. Tables 8.5, 8.6 and 8.7 provide the parameters used, run time, cost functions and spatial compactness (number of patches) for random and greatest difference initial input solutions for all three grids of ordinal, continuous and fuzzy cost models, respectively.

In the small grid, the cost functions did not improve more than the values in the table in the greatest difference initial input solution for all cost models and were taken to be optimum solution. The algorithm could not reach to the global cost function in the medium grid and large grids. However, the near-optimal solution in the greatest difference initial input solution had a lower cost function than in the random initial solution for all the cost models in the medium grid. In the large grid, the algorithm produced more improvement in the cost function for the random initial solution than in the greatest difference initial solution in the continuous and fuzzy cost models. The maximum improvement in the cost function was found in the fuzzy cost models in both initial input solutions for all the grid sizes.

The algorithm generated the solution with the lowest number of patches in the small and medium grids using the continuous cost models. In the case of the large grid, the fuzzy cost model gave the highest spatial compactness with the lowest number of patches among all cost models. The near-optimum land use allocation to the small, medium and large MOLAA problems are shown in Figures 8.7 for the random initial input solution of the ordinal cost model.

Table 8.5 Cost functions closest to the global cost functions for all three grids of ordinal cost model

S. N.	Grid size	Parameters T_L	S_R	Run time *h:m*	Near optimum Cost function	Cost function Reduction %	Spatial compactness
				Random input grids			
1	Small	10	10,000	<0:01	40940	12.917	10
2	Medium	10	2,885,700	0:06	4153840	21.499	374
3	Large	10	55,835,400	4:25	68285913	26.988	4146
				Greatest difference input grids			
1	Small	10	10,000	<0:01	40793*	9.939	14
2	Medium	10	2,885,700	0:06	4153500	8.952	374
3	Large	10	55,835,400	5:22	68285913	10.932	4102

Note: The symbol * indicates the optimum cost function.

Table 8.6 Cost functions closest to the global cost functions for all three grids of continuous cost model

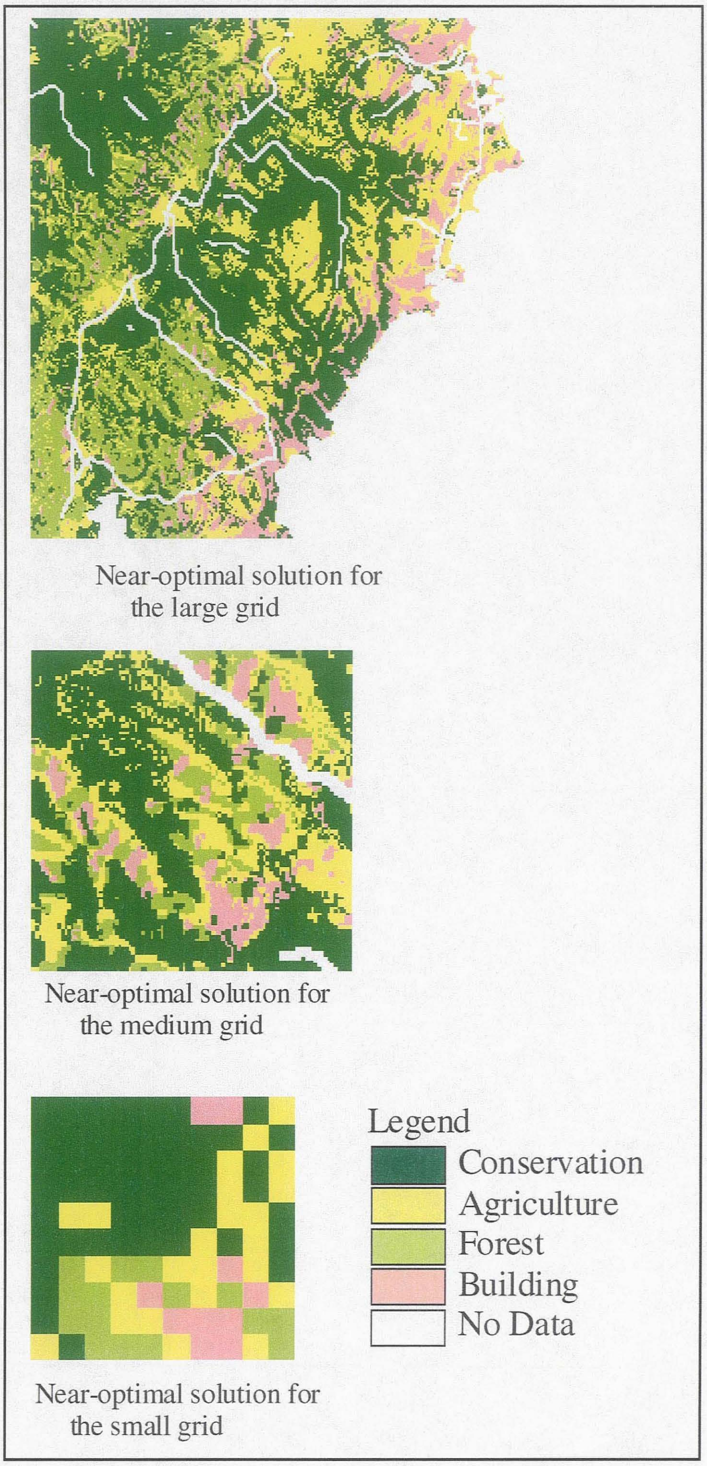
S. N.	Grid size	Parameters T_L	S_R	Run time *h:m*	Near optimum Cost function	Cost function Reduction %	Spatial compactness
				Random input grids			
1	Small	10	10,000	<0:01	75850*	15.508	9
2	Medium	10	2,885,700	0:06	7512972	16.219	283
3	Large	10	55,835,400	25:01	129703154	21.898	3412
				Greatest difference input grids			
1	Small	10	10,000	<0:01	75850*	5.318	10
2	Medium	10	2,885,700	0:07	7512284	8.098	274
3	Large	10	55,835,400	32:39	129702953	19.030	3417

Note: The symbol * indicates the optimum cost function.

Table 8.7 Cost functions closest to the global cost functions for all three grids of fuzzy cost model

S. N.	Grid size	Parameters T_L	S_R	Run time *h:m*	Near optimum Cost function	Cost function Reduction %	Spatial compactness
				Random input grids			
1	Small	10	10,000	<0:01	249764	19.291	11
2	Medium	10	2,885,700	0:08	29616156	27.492	298
3	Large	10	55,835,400	16:30	451320822	36.450	3133
				Greatest difference input grids			
1	Small	10	10,000	<0:01	248292*	5.621	12
2	Medium	10	2,885,700	0:09	29612597	18.969	281
3	Large	10	55,835,400	10:33	451321533	23.036	3140

Note: The symbol * indicates the optimum cost function.



Near-optimal solution for the large grid

Near-optimal solution for the medium grid

Near-optimal solution for the small grid

Figure 8.7 Near-optimal land use allocation in the small, medium and large MOLAA problems by Tabu Search using random initial input solution of the ordinal cost suitability model

8.1.6 Assessing performance of Tabu Search in solving the MOLAA problem

8.1.6.1 Analysing the spatial compactness without compactness function

Table 8.8 presents the number of patches with corresponding cost functions for the large grid, applying the algorithm at Tabu length (T_L) = (25) and four swapping rates in the random initial input solution of all three cost models. The lower number of patches implies a higher level of spatial compactness. The land use allocation in the fuzzy cost model was found to be more spatially compact than in the continuous and ordinal cost models similar to the Simulated Annealing (see Section 7.1.5.1 in Chapter 7). In general the total number of patches decreased with an improvement in the cost function in all the cost models. Nevertheless, for a small difference in the cost function, the spatial compactness may be more enhanced even at the higher cost function. The Tabu Search produced similar spatial compactness as the Simulated Annealing using different cost models in the medium grid (see Section 7.1.5.1 in Chapter 7).

Table 8.8 Number of patches (N_P) at different parameters for the random input model of medium grids

Total cost function for ordinal model = 68283000+
Total cost function for continuous model = 129703000+
Total cost function for fuzzy model = 451319000+

Swapping rate	Cost model					
	Ordinal		Continuous		Fuzzy	
	Cost function	No. of patches	Cost function	No. of patches	Cost function	No. of patches
186118	5486	4397	18062	3593	33220	3229
1861180	3651	4204	10038	3476	11859	3150
9305900	2936	4088	3767	3447	5000	3142
18611800	3742	4132	1940	3421	3717	3144

Note: The spatial compactness was generally enhanced with the improvement in the cost function and the algorithm produced more spatially compact land use allocation using the fuzzy cost model.

8.1.6.2 Computation time

In the Tabu Search, computational time was mainly determined by the swapping rate, the search strategy (whether it is static or dynamic), and the size of the problem. However, at the same swapping rate, the run time was also influenced by Tabu length. The average computation times at four Tabu lengths and four swapping rates are given in Table 8.9, using the random initial input solution of all the cost models in the medium grid. The computation time less than the nearest minute is indicated by the less than sign (<). The computation time increased with the higher value of Tabu length for the same swapping rate. The run time was the highest in the fuzzy cost model followed by the continuous cost model.

Table 8.9 Average run time for the random input model of the medium grid size for all cost models

Swapping rate	$T_L = 48$			$T_L = 96$		
	Ordinal	Continuous	Fuzzy	Ordinal	Continuous	Fuzzy
9619	<0:01	<0:01	<0:01	<0:01	<0:01	<0:01
96190	<0:01	<0:01	<0:01	<0:01	<0:01	<0:01
480950	<0:02	<0:02	0:02	<0:02	<0:03	<0:03
961900	<0:03	0:03	0:03	0:03	0:04	0:04
Swapping rate	$T_L = 241$			$T_L = 481$		
	Ordinal	Continuous	Fuzzy	Ordinal	Continuous	Fuzzy
9619	<0:01	<0:01	<0:01	<0:01	<0:01	<0:01
96190	<0:01	<0:01	<0:01	0:01	<0:02	<0:02
480950	<0:03	<0:04	<0:04	0:04	0:05	0:06
961900	0:05	0:06	0:06	0:08	0:09	0:10

The run time increased markedly in the large size MOLAA problem. It increased with the higher values of the Tabu length and swapping rate as in the medium grid. For instance, this is shown in Figure 8.8, applying the algorithm with Tabu lengths (T_L) = (931, 1862, 4653, 9306) at three swapping rates (S_R) = (9619, 96190 and 480950) in the large grid MOLAA problem. The algorithm with parameters (T_L, S_R) = (4653, 480950) did not deliver a solution in more than 48 hours and was deliberately terminated. Although the run times varied for the same parameter setting, input solution and cost model, Tabu Search generated solutions in the lowest time in the ordinal cost model in all input solutions for the same parameters.

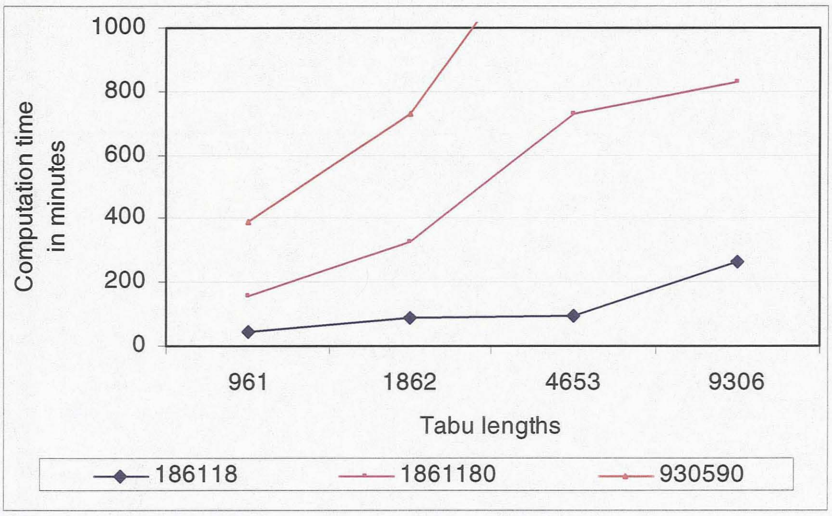


Figure 8.8 Computation time for four Tabu lengths at different swapping rates for the large grid in ordinal cost model

8.1.7 Appropriate parameters for Tabu Search

The algorithm delivered a near-optimum solution for a small grid (10 by 10 cells) problem in less than a minute using a Pentium IV PC. In the case of the medium grid (100 by 100 cells) problem, the algorithm delivered a near-optimal solution in less than ten minutes for all the cost models. However, the algorithm with parameters (T_L, S_R) = (10, 50*V_C) produced a solution similar to the near-optimal solution in less than two minutes computation time in the medium grid.

In the large grid MOLAA problem, the Tabu length (T_L) = (10) and the highest swapping rate (S_R) = (300*V_C) that is, 55,835,400 were used in the algorithm to generate the near-optimum solution in the large grid. It took more than four hours to generate a solution using the random initial solution in the ordinal cost model (see Section 8.1.5). However, the algorithm at the swapping rates (S_R) = (50*V_C) and (S_R) = (100*V_C) could produce a solution close to the near-optimal solution in much less time. Hence the Tabu lengths (T_L) = (10) at swapping rates (S_R) = (50*V_C) and (S_R) = (100*V_C) were used in the algorithm in solving a MOLAA problem in the random input model of the ordinal cost model in the large grid. The solutions were compared in the terms of the cost function, spatial compactness and run time with the near-optimal solution (Table 8.10).

Table 8.10 Difference in cost functions, run time and compactness between two different swapping rates at different Tabu lengths in the large grid

Total cost function = 68285000+

Parameters		Cost function			Spatial compactness		Run Time *h:m*	
T_L	S_R	Average	Change	% Change	Average	Change	Average	Saving
10	50	1228	315	0.000461	4127	- 19	1:33	7:00
10	100	1108	195	0.000285	4134	- 12	2:32	5:59

The mean values of cost function and the spatial compactness did not differ significantly between the solutions produced at these parameter settings. The small value of Tabu length (T_L) = (10) reduced the computation time to about two and half hours. However, the algorithm with the swapping rate (S_R) = (50*V_C) delivered the solution about an hour quicker than at the swapping rate (S_R) = (100*V_C). Hence the algorithm with parameters (T_L, S_R) = (10, 50*V_C) was found to be appropriate for solving a MOLAA in the large grid problem.

8.1.8 Applying compactness function in the algorithm

The compactness function was applied using compactness factors (F_C) = (25, 50, 75, 100 and 200) in the Tabu Search algorithm with appropriate parameters (T_L, S_R) = (10, 50*V_C). The cost function, run time and spatial compactness in terms of number of patches in eight neighbour rule are given for the medium and the large grids using random initial input solution of the ordinal cost model in Tables 8.11 and 8.12, respectively. The use of compactness factors (F_C) = (25, 50, 75, 100 and 200) in the Tabu Search algorithm increased the spatial compactness in both grids.

Table 8.11 Spatial compactness after applying compactness function in the medium grids of ordinal cost model

Total cost function = 4153000+

Compactness Factor	Random			Greatest		
	Cost function	Run time, *h:m*	No. Of patches	Cost function	Run time, *h:m*	No. of patches
0	853	<0:02	384	650	<0:02	376
25	67559	0:02	100	65032	0:02	111
50	121047	0:02	72	120624	0:02	78
100	212745	0:02	65	220527	0:02	58
200	331286	0:02	51	300305	0:02	66

Table 8.12 Spatial compactness after applying compactness function in the large grids of ordinal cost model

Total cost function = 68285000+

Compactness Factor	Random			Greatest		
	Cost function	Run time, *h:m*	No. Of patches	Cost function	Run time, *h:m*	No. of patches
0	1309	1:33	4120	881	1:44	4126
25	1309740	1:03	918	1295163	1:02	934
50	2179927	1:16	300	2182540	1:21	688
100	3269845	1:46	565	3321778	1:59	551
200	4408792	4:10	424	4565176	2:49	498

8.1.9 Appropriate input model and cost model for Tabu Search

Tabu Search algorithm with parameters (T_L, S_R) = (10, 50*V_C) was applied to the MOLAA problem in the medium and large grid size, respectively. The algorithm was implemented in three initial input solutions of the ordinal, continuous and fuzzy cost models. The average cost functions, run time and spatial compactness are given for these input solutions and cost model in Table 8.13. Among the three initial input solutions, the cheapest and the greatest difference input solutions produced significant improvement in the cost function than the random input solution in the medium grid MOLAA problem for all the cost models. In the large grid, the algorithm minimized the cost function more in the random initial input solution than in the cheapest and greatest difference initial input solutions in the continuous cost model and the mean cost functions were found to be significantly different at 95 percent confidence interval. In the fuzzy cost model, the minimization of the cost function did not differ significantly among the three initial input solutions whereas in the ordinal cost model, the mean cost function between the random and greatest difference initial input solutions were found to be significantly different at 95 percent confidence level. Regarding the null hypothesis about the initial input solutions, it was rejected in the medium grid and the continuous and ordinal cost models of the large grid. But there was not enough evidence to reject the hypothesis in the case of the fuzzy cost model of large grid.

The algorithm did not produce consistent result on spatial compactness in the medium grid using different cost models (see Section 8.1.6.1). However, the spatial compactness was the highest in the fuzzy cost model for the MOLAA problem in the large grid. The mean values of number of patches in the solutions were found to be significantly different among the three cost models for both grid sizes. Thus these findings reject the null hypothesis about the influence of the cost models on spatial compactness.

Table 8.13 Comparing the average cost functions, run time and spatial compactness for all the input models and cost models in the medium and large grid MOLAA problem

Cost model	Initial Input solution	Medium Grid			Large Grid		
		Average cost function	Average Run time h:m	Average number of patches	Average cost function	Average Run time h:m	Average number of patches
Ordinal	Random	4153827	<0:02	377	68286228	1:33	4122
	Cheapest	4153550	<0:02	377	68285883	1:27	4131
	Greatest	4153563	<0:02	383	68285937	1:36	4132
Continuous	Random	7512999	<0:02	277	129706610	7:19	3440
	Cheapest	7512351	0:01	280	129706995	7:51	3446
	Greatest	7512372	<0:02	279	129707693	6:39	3453
Fuzzy	Random	29616093	<0:02	299	451324501	3:39	3141
	Cheapest	29612639	<0:02	301	451324659	3:17	3144
	Greatest	29612686	<0:02	299	451324715	3:56	3141

8.2 Discussion

Two search strategies with a static (fixed swapping rate) and dynamic (variable swapping rate) mode were applied in the Tabu Search algorithm. Despite the higher swapping rate in the dynamic mode, the cost function minimization in both modes did not differ significantly for the same swapping rate. In the dynamic mode, the algorithm is likely to have a higher swapping rate, as the swapping rate is randomly selected between the specified swapping rate and twice the specified swapping rate. For instance, if the specified swapping rate was 96,190, a swapping rate between 96,190 and 192,380 would be chosen in the dynamic mode. The algorithm with dynamic mode requires more computation time than the algorithm with static mode, because of the additional time needed for random selection of the land units for higher numbers of swapping rates in each iteration in the dynamic mode than in the static mode.

Searching for a new solution which reduces the cost function is vital to optimization, ultimately delivering a solution with minimum cost function. This study compared the influence of the three neighborhood sizes (N_S) = (1, 4 and 8) on improving the cost function, using the Tabu Search algorithm. The large neighborhood sizes (N_S) = (4 and 8) significantly improved the cost function at the lower swapping rates (S_R) = (=<10*V_C) than the single neighbourhood that is (N_S) = (1). However, there were no significant differences in the mean cost function among these neighbourhood sizes at the higher swapping rates (S_R) = (=>50*V_C). It implies that the algorithm at the large neighbourhood sizes (N_S) = (4 and 8) selected four or eight potential land units at each iteration and evaluated before selecting the best neighbourhood for swapping the land uses whereas only one land unit was selected in the single neighbourhood. Therefore, the algorithm at the higher neighbourhood sizes improve the cost function more at the lower swapping rates (S_R) = (=<10*V_C) than the algorithm with single neighbourhood. However, at the higher swapping rate, even the single neighbourhood size could search for all spaces and improve the cost function as more as the algorithm at the higher neighbourhood sizes. The algorithms with the higher neighbourhood sizes were not found efficient in terms of the computation time taken by the algorithm as compared to the algorithm with the single neighbourhood. The computation time increased with the higher neighborhood sizes, requiring an additional time for selection of the specified number of potential neighborhood solutions and their evaluation, in order to find the best neighborhood solution.

The main characteristic of Tabu Search is to restrict cycling or repetition of previous moves in search of an optimum solution, while avoiding entrapment in a local solution (Topaloglu, 2004). Different values of Tabu length were tested on their influences on cost function minimization in a MOLAA problem. The small and large values of Tabu lengths were found to have same impact on the cost function. For instance, the Tabu lengths (T_L) = (2405) and (T_L) = (48) exert no significant difference on the mean cost functions at 95 per confidence interval in the medium grid. However, the higher Tabu length markedly increased the computation time in order to maintain the larger list and also taking time to check whether a randomly selected land unit is in the list or not.

In this research the location of the selected land unit was defined as 'Tabu' and registered in the Tabu list. The list prevented the reversal of the previsous moves by restricting the swapping of the land units already included in the list. However, it could not prevent the swapping of land uses between the land units at other locations with the same cost. The idea of using location attribute for defining 'Tabu' may be very consersative to a MOLAA problem. Other attributes like the land use and the cost value should be used in the Tabu list and their influence on the cost function minimization should be compared with the result using location attributes in the Tabu list.

The swapping rate was found to be the most influential parameter in the algorithm by controlling the efficiency and effectiveness of the Tabu Search algorithm. The swapping rate determines the number of land use exchange between two land units per step. The swapping of land uses functionally contributes to the cost function minimization. The higher swapping rate contributed to the better improvement in the cost function. However, the swapping rates higher than (S_R) = ($50*V_C$) did not improve the cost function significantly. The run time increased with increasing numbers of swapping rates. A compromise of run time and cost function was taken to decide on an appropriate swapping rate for the MOLAA problem.

8.3 Conclusion

The Tabu Search algorithm was successfully applied to solving a MOLAA problem. The appropriate parameter values and input requirements were also searched for this algorithm and the results were discussed. By applying the Tabu Search algorithm to three different grid sizes (small, medium and large) MOLAA problems at different search strategies, neighbourhood sizes, Tabu lengths and swapping rates, this study has drawn the following conclusions.

1. The Tabu Search algorithm was found to perform more efficiently in the static mode than in the dynamic mode. Although the algorithm in the dynamic mode executed more swaps per step than the static mode for the specified swapping rate, there was no significant difference in the mean cost functions for the solutions reached by the algorithm in these two modes. However, the higher number of swaps in the dynamic mode and also the selection of the number of swaps per step randomly for each step contributed to the higher computation for delivering a solution by the algorithm in the dynamic mode.

2. Among the three neighbourhood sizes (N_S) = (1, 4 and 8) used in the Tabu Search, the algorithm with single neighbourhood size, that is, (N_S) = (1), produced an efficient solution to a MOLAA problem. The algorithm at the higher neighbourhood size (N_S) = (4 and 8) improved the cost function more at the lowest parameters (T_L, S_R) = (962, 1*V_C) than at the neighbourhood size (N_S) = (1). The difference in the mean cost function became smaller with increasing swapping rates but the computation time increased dramatically with the higher Tabu lengths and swapping rates.

3. Different Tabu lengths were found to be indifferent to the cost function minimization in solving a MOLAA problem. However, the higher Tabu lengths contributed markedly to the rise in the computation time in delivering a solution by the Tabu search. Therefore, the algorithm at the lowest value of the Tabu length was found to be more efficient than using the higher Tabu lengths.

4. In the Tabu Search algorithm, the key parameter was found to be the swapping rate for minimizing the cost function in solving a MOLAA problem. The cost function was found to be improved with the higher values of the swapping rates. However, the rate of improvement tends to decrease with the higher swapping rates and the swapping rate higher than (S_R) = (>=50*V_C) may not improve the cost function significantly.

5. The Tabu Search algorithm was successfully applied to a MOLAA problem using the three initial input solutions generated by the random, cheapest and greatest difference methods. The Tabu Search algorithm improved the cost function more using the cheapest and greatest difference initial input solutions than the random input solution in the medium grid. However, in the large grid MOLAA problem, the algorithm minimized the cost function better using the random input solution than in the cheapest and greatest difference input solutions derived from the continuous and fuzzy models.

6. An optimum or near-optimum solution to a MOLAA problem was generated by applying the Tabu Search algorithm with the parameters $(T_L, S_R) = (10, 300^* V_C)$, $(10, 300^* V_C)$ and $(10, 300^* V_C)$ for the small, medium and large grid MOLAA problems, respectively. The algorithm generated the optimum solution for the small grid using the greatest difference initial solution for all the data types.

7. The computation time for the Tabu Search algorithm was found to be largely dependent on the Tabu length, swapping rate and the grid size of a MOLAA problem in the static mode. The computation time to deliver a solution by the Tabu Search algorithm rose with the higher values of the Tabu length, swapping rate and the grid sizes. Among the three models, the algorithm required the highest computation time in the fuzzy model, followed by the continuous model. The algorithm delivered the solution in the quickest time to a MOLAA problem in the ordinal model. In three initial input solutions, the algorithm took longest time in the greatest difference input solution and then, in the cheapest input solution and the least time was required for the random input solution.

8. An appropriate parameter was suggested for the Tabu Search algorithm in solving a MOLAA problem. In the small grid, the algorithm with parameters $(T_L, S_R) = (10, 100^* V_C)$ could deliver an optimum solution in less than one minute computation time. The Tabu Search with parameters $(T_L, S_R) = (10, 50^* V_C)$ was found appropriate for the medium and large MOLAA problems.

9. Based on the computational efficiency and the spatial compactness, the fuzzy cost model with any of three initial input solutions could be appropriate in solving a large grid MOLAA problem. In the case of the medium grid, the algorithm also

produced better solution in fuzzy models with highest improvement in the cost function. Therefore, the fuzzy cost model with the cheapest or greatest difference initial input solution could be the appropriate choice.

8.4 Summary

This chapter demonstrated the application of the Tabu Search algorithm in solving a MOLAA problem. A hypothetical MOLAA problem was successfully solved by applying the Tabu Search algorithm to three different initial solutions of the ordinal, continuous and fuzzy cost models. Table 8.14 presents a summary of the parameters, comments on the null hypothesis and the findings.

Table 8.14 A summary of the parameters, their descriptions and hypothesis

Parameters	Comment on null Hypothesis	Findings
Search Strategy	Accepted	Although the dynamic strategy used the higher numbers of swaps, the cost function was not improved significantly between static and dynamic search strategies.
Neighbourhood size	Conditionally accepted	The higher neighbourhood size significantly improved the cost function at the lower swapping rates but the mean cost functions did not differ significantly at the swapping rates (S_R) = (=>50*V_C). Hence, the null hypothesis was accepted at the higher swapping rates.
Tabu length	Accepted	Different Tabu length did not influence on the cost function minimization, but the higher Tabu length increased the computation time. The cost functions at differ Tabu length were not significantly different among different Tabu length.
Swapping rate	Rejected	The numbers of hot-swaps and cold-swaps acceptances were determined by the swapping rate. Thus the algorithm improved cost function more at the higher swapping rates (S_R)= (=>50*V_C) at the lower swapping rates (S_R) = (=>10*V_C).
Compactness function	Rejected	The higher values of compactness factor produced better spatial compactness in all cost models by accepting the move that increased the spatial compactness.
Initial input model	Rejected	The algorithm delivered solutions with lower cost function using the cheapest and greatest difference initial input model in the medium grid whereas in the large grid, the algorithm minimized the cost function better in the random input model.
Cost model	Rejected	The algorithm produced a more spatially compact land use allocation using fuzzy model than in other models in the large grid.

Regarding the parameters for the Tabu Search, the lowest value of Tabu length (T_L) = (10) and the swapping rate (S_R)= (50*V_C) were found to be appropriate in solving a MOLAA problem. The fuzzy cost model with random initial input solution was found to be suitable model for applying Tabu Search based on the improvement in the cost function and the spatial compactness. The performance of this algorithm will be compared with the MOLA module and the Simulated Annealing in Chapter 9.

Chapter 9

COMPARING THE GIS BASED MOLA AND COMBINATORY METHODS

This chapter presents a comparison of the MOLA module and two combinatory methods in solving the MOLAA problem. The performance of these methods in solving the MOLAA problem was compared in terms of the quality of the solution, run time and spatial compactness. In order to compare the quality of the solutions by these methods, the cost function for the solution obtained from the MOLA module was derived by summing up the cost suitability values for the allocated land use to all land units (see Chapter 5). In addition, the combinatory methods are also compared in terms of enhancing spatial compactness by incorporating a compactness function in both algorithms. These comparisons should provide an informed choice of method in solving a MOLAA problem to decision makers, planners and the concerned stakeholders.

9.1 Results

9.1.1 Comparing the solutions to the MOLAA problem by Combinatory methods and MOLA module

9.1.1.1 Cost function as a measure of overall of land use suitability

Tables 9.1 and 9.2 present the cost range and the total cost values for the land units allocated to different land uses by the MOLA module, Simulated Annealing and Tabu Search by the ordinal and continuous models, respectively. The combinatory methods produced a lower cost function than the MOLA in both models. The cost function arrived at by the MOLA exceeded the combinatory method's cost function by more than 13 and 7.5 percent in the ordinal and continuous models, respectively. Within the combinatory methods, the mean cost functions between the Simulated Annealing and Tabu Search did not differ significantly at 95 percent confidence interval for all three initial input solutions. However, the cost functions were slightly more improved by the Simulated Annealing than by Tabu Search in all models.

Table 9.1 Cost suitability values in the output from MOLA, SA and TS using ordinal model

Land use Type	MOLA			Simulated Annealing			Tabu Search		
	Min	Max	Total	Min	Max	Total	Min	Max	Total
Conservation	223	1000	52561783	223	675	41698694	223	675	41703102
Agriculture	200	333	12841213	200	434	13374134	200	434	13370883
Forestry	200	253	6578076	237	400	7478016	237	400	7479408
Development	223	363	5301079	223	450	5734954	223	450	5732916
Cost Function	77282151			68285798			68286309		

Table 9.2 Cost suitability values in the output from MOLA, SA and TS using continuous model

Land use Type	MOLA			Simulated Annealing			Tabu Search		
	Min	Max	Total	Min	Max	Total	Min	Max	Total
Conservation	462	1562	90054146	462	1219	78321890	462	1219	78334039
Agriculture	392	671	25679767	392	800	25380751	392	800	25386140
Forestry	414	552	14342803	505	653	15677590	505	653	15677238
Development	417	541	9371998	433	720	10324715	433	710	10308885
Cost function	139448714			129704946			129706302		

At the land use levels, the total suitability costs for agriculture, forestry and development uses were found to be lower in the solution reached by the MOLA than that of the combinatory methods in the ordinal model. The higher cost function achieved by the MOLA module was actually due to a less suitable land use allocation for conservation in both ordinal and continuous cost models.

In the case of the combinatory methods, the Simulated Annealing and Tabu Search allocated the same range of cost values for all land uses (see Tables 9.1 and 9.2). The cost functions were more improved in the land use allocations by Simulated Annealing than by Tabu Search in all cost models (see Tables 7.17 in Chapter 7 and 8.13 in Chapter 8). Although Tabu Search produced a near optimal solution much more quickly than Simulated Annealing at the same swapping rates, these solutions were not as satisfactory as the solutions by the Simulated Annealing (see Section 7.1.4 in Chapter 7 and Section 8.1.5 in Chapter 8).

Tables 9.3 and 9.4 illustrate the consistency in land use allocation by three different methods for the ordinal and continuous models. Simulated Annealing and Tabu Search produced consistently similar land use allocation, but both produced quite different land use allocation to the MOLA method. For instance, the Simulated Annealing and the Tabu Search allocated more than 99 percent land units with the same land uses in the continuous model (see Table 9.4).

Table 9.3 Consistency in land use allocation between different methods in the ordinal cost suitability model

Land use Type	MOLA-Simulated Annealing		MOLA-Tabu Search		Simulated Annealing-Tabu Search	
	#of cells	Percent	#of cells	Percent	#of cells	Percent
Conservation	63321	68.04	63335	68.06	92709	99.62
Agriculture	29305	62.98	29319	63.01	44871	96.44
Forestry	8870	31.77	8909	31.91	26036	93.26
Development	11980	64.37	11972	64.32	18303	98.34
Total	113476	60.97	113535	61.00	181919	97.74

Table 9.4 Consistency in ideal land use allocation between different methods in the continuous cost suitability model

Land use Type	MOLA-Simulated Annealing		MOLA-Tabu Search		Simulated Annealing-Tabu Search	
	#of cells	Percent	#of cells	Percent	#of cells	Percent
Conservation	68184	73.27	68223	73.31	92905	99.83
Agriculture	33153	71.25	33173	71.29	46324	99.56
Forestry	11387	40.79	11338	40.61	27711	99.26
Development	7363	39.56	7431	39.92	18414	98.94
Total	120087	64.52	120165	64.56	185354	99.59

In the combinatory methods, minimization of the cost function was attributed to the acceptance of the cold-swaps and hot-swaps. Figure 9.1 compares the acceptance of these moves (hot-swaps and cold-swaps) between the Simulated Annealing and Tabu Search at the appropriate parameters for the ordinal models. The role of cold-swaps and hot-swaps in the cost function minimization for both algorithms is illustrated in Figure 9.2. Figure 9.3 displays the cost minimization by the cold-swaps only after the hot-swaps become zero and the number of cold-swaps per step that solely improve the cost function after all the hot-swaps were rejected by the algorithm, is shown in Figure 9.4. Although the acceptance of hot-swaps and cold-swaps was dependent on the parameters used in the algorithms, the cost function in the final solution was about the same for both the Simulated Annealing and Tabu Search.

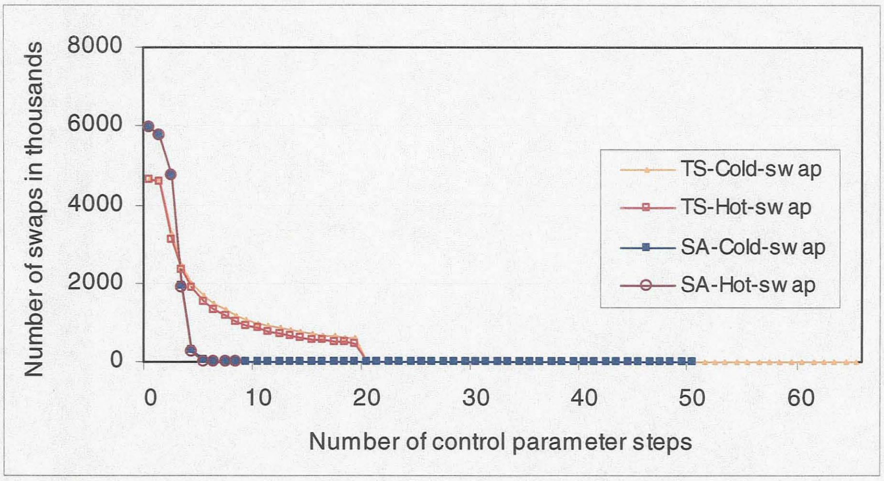


Figure 9.1 Comparing the acceptance of hot-swaps and cold-swaps using the appropriate parameters between the Simulated Annealing and Tabu Search

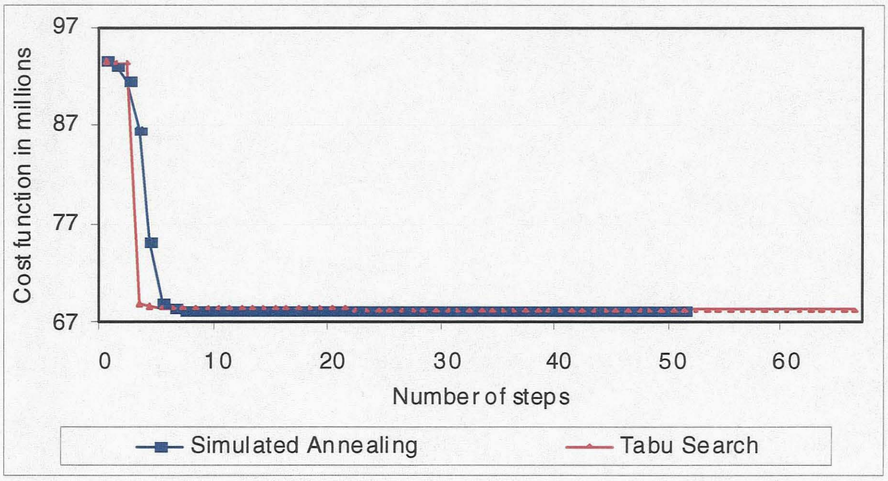


Figure 9.2 Comparing the cost functions using the appropriate parameters between the Simulated Annealing and Tabu Search

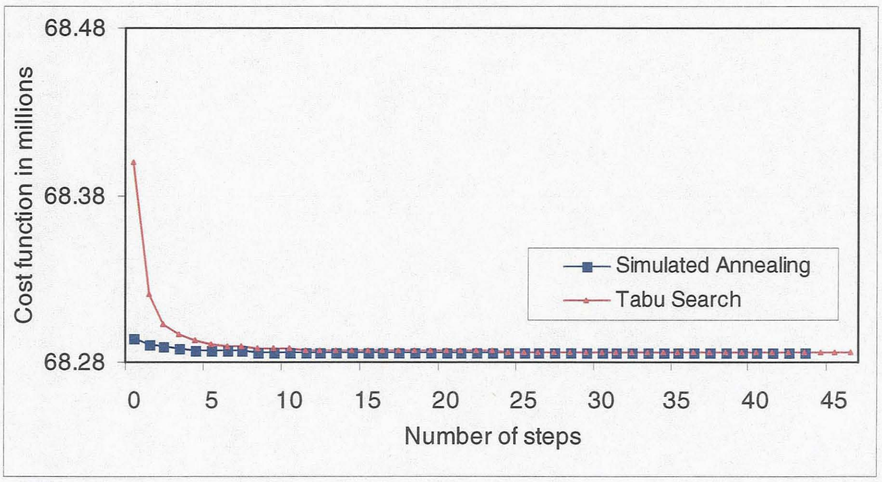


Figure 9.3 Comparing the cost functions minimization by the cold-swaps only between the Simulated Annealing and Tabu Search

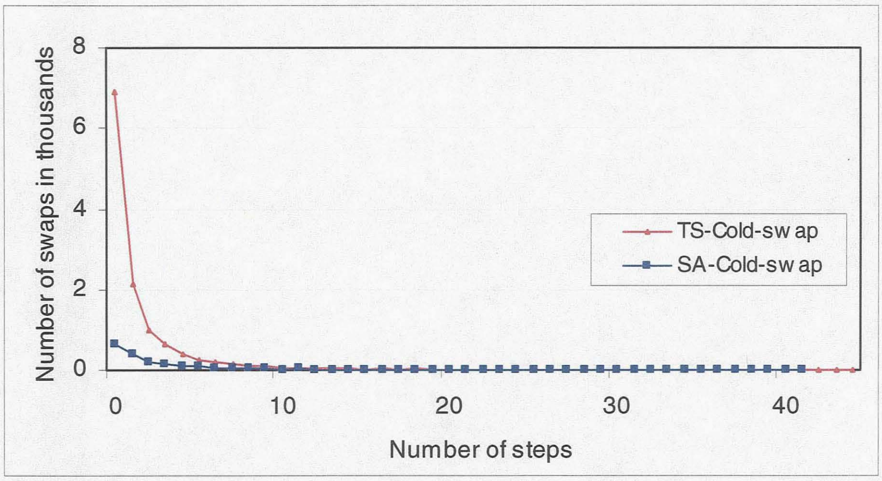


Figure 9.4 Comparing the acceptance of the cold-swaps per step after the hot-swaps became zero in the Simulated Annealing and Tabu Search

9.1.1.2 Spatial compactness a desirable criterion for land use allocation

Figures 9.5 and 9.6 display a comparison of the spatial compactness in terms of the number of patches (N_P) in the solutions by the MOLA module and the combinatory methods in the ordinal and continuous models, respectively. The combinatory methods produced better spatial compactness than the MOLA module for both models. Within the combinatory methods, the two methods produced similar spatial compactness in both models. In comparison to the MOLA module, land use allocation by the combinatory methods was found to be about 16 percent more compact in the ordinal model and about 5 percent more compact in the continuous model. However, the land use allocation by the MOLA module produced higher spatial compactness for conservation land use than the combinatory methods in both models.

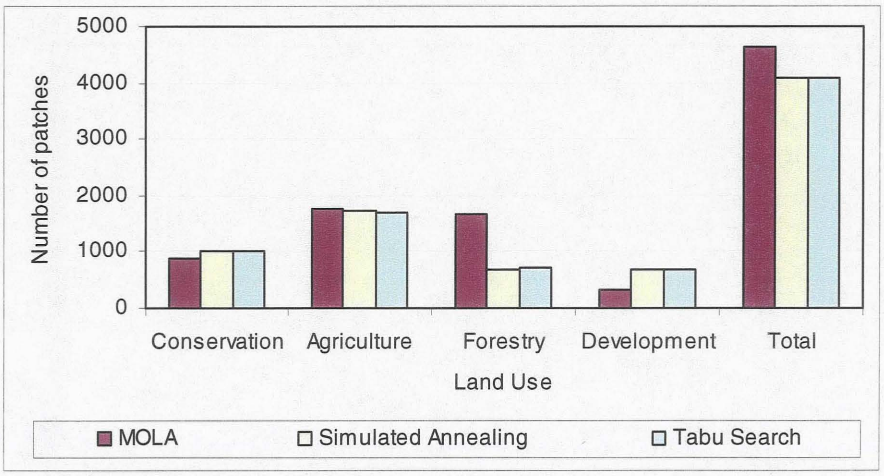


Figure 9.5 Spatial compactness by three methods in the ordinal model

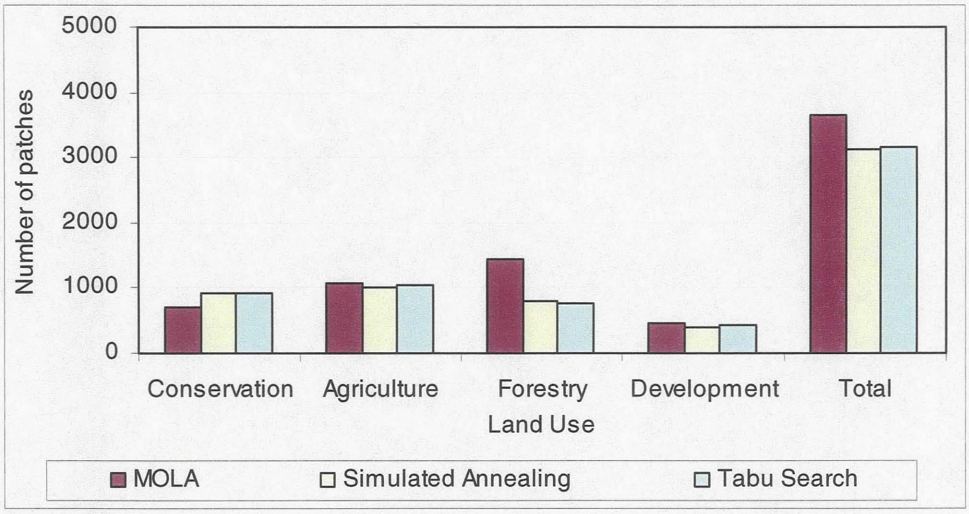


Figure 9.6 Spatial compactness by three methods in the continuous model

9.1.1.3 Computation time as a measure of efficiency of the methods

Regarding the efficiency of these methods, the MOLA module generated a solution to the large size MOLAA problem in less than two minutes using a Pentium IV PC. For this solution, Simulated Annealing took on average one hour and fifty-four minutes for the ordinal model and two hours and forty-three minutes for the continuous model, using the random initial input solution (see Table 7.17 in Chapter 7). Tabu Search delivered the solutions in an average computation time of an hour and half in the ordinal model and seven hours nineteen minutes in the continuous model using the random initial input solution (see Table 8.13 in Chapter 8). Using the fuzzy model, Simulated Annealing delivered a solution in an average of two hours and forty-one minutes whereas Tabu Search took one hour more than Simulated Annealing. For the medium grid MOLAA problem, the computation time was less than one minute for the MOLA module and Simulated Annealing, whereas the Tabu Search delivered a solution in about two minutes.

9.1.2 Adding compactness function into the combinatory methods

Table 9.5 compares the number of patches that resulted in the solutions by applying the Simulated Annealing and Tabu Search algorithms with different values of compactness factors, using the greatest difference initial input solution of all models in the medium grid. The Simulated Annealing produced better spatial compactness for the same values of compactness factors in all models except the Tabu Search in the medium grid.

Table 9.5 Spatial compactness at different compactness factor for the combinatory methods in the medium grid

Compactness factor	Simulated Annealing			Tabu Search		
	Ordinal	Continuous	Fuzzy	Ordinal	Continuous	Fuzzy
25	73	92	133	100	131	151
50	53	62	106	72	95	114
100	37	47	103	65	68	123
200	32	35	70	51	65	102

9.2 Discussion

In solving the same MOLAA problem, the combinatory methods produced a lower cost function than the MOLA module in the ordinal and continuous models. This result can be attributed to the difference in the technique and the decision rule applied to solve the land use allocation problem. These combinatory methods are, in fact, approximation optimisation techniques and minimize the cost function in the final solution by allocating the cheapest possible land use to each land unit. Unlike these combinatory methods, the MOLA module is not an optimisation technique, rather it uses a fixed decision rule to allocate land use with the lowest rank value (in descending order, with rank value 1 the most suitable) to each land unit. This rule is found to be biased towards the lesser area requirement land uses by allocating more suitable land units to them (discussed in Chapter 6). In this hypothetical problem, if agriculture, forestry and development land uses were taken into consideration, the MOLA module produced a better result than the combinatory methods. However, the conservation land use which had the highest area requirement was allocated with less suitable land units and contributed to the higher cost function in the solution reached by the MOLA.

The MOLA module uses a deterministic decision rule and produces the same land use allocation using the same rank maps (discussed in Chapter 6), but these combinatory methods rely on the iterative improvement of the cost function by exchanging land uses between randomly selected land units. Hence the algorithms with the same parameters may not produce the same cost function and spatial pattern in two independent runs. Nevertheless, both algorithms could produce the solution with the same cost function even at different parameters for the small grid (10 by 10 cells) MOLAA problem (see Chapters 7 and 8). This is because the algorithm is able to search all land units for the best possible land use and can allocate the same land use to each land unit. In the medium or large grid, the algorithms could not do this because of large possible combinations of decision variables (land uses and land units) and therefore, could not allocate the same land use to each land unit and produce different cost functions and spatial patterns in different runs. However, the Simulated Annealing and Tabu Search produced similar cost functions and higher consistency by allocating the land units with the same land uses for the same cost suitability models (ordinal, continuous and fuzzy).

The combinatory methods produced overall more compact land use allocations for the four land uses than the MOLA module. Spatial compactness is enhanced by allocating the adjoining land units with the same land use, that is, by reducing the number of patches under a single land use. However, there is a trade off between the spatial compactness and the cost function. Allocating the adjoining land units with the same land use despite the higher cost value increases the spatial compactness, but it also increases the cost function. This is exemplified by the MOLA module, which produces a solution with a better spatial compactness for conservation land use by allocating less suitable land units than if the combinatory methods were used for both models. Although the combinatory methods produced a less compact land use allocation for conservation land use than the MOLA module, the spatial compactness achieved for agriculture and forestry land uses with the higher cost than the MOLA module (see Tables 9.1 and 9.2) accounted for the overall more spatially compact land use allocation by the combinatory methods.

The MOLA module was found to be very efficient compared to the combinatory methods in terms of computation time taken to deliver a solution to a MOLAA problem. It takes a short time to compare the rank values among the land uses in each land unit and assigns the land use with the best rank value. Unlike the MOLA module, the combinatory methods randomly search for the suitable land use for each land unit by swapping land uses for a specified number of swaps in each step until the stopping criterion is met. In the case of the combinatory methods, the run time increases with the size, swapping rate and variability in the input cost models. Despite half the swapping rate ($S_R = 50^* V_C$) being used in the Tabu Search of that in the Simulated Annealing ($S_R = 100^* V_C$), the former algorithm requires six-seven times more steps to reach the stopping criterion in the continuous model. Maintaining, updating and checking of the Tabu list and also the preventing the land use swapping between the same land use in the Tabu Search algorithm may have contributed to the higher computation time than in the Simulated Annealing. Thus the Tabu Search takes more than double the time taken by the Simulated Annealing in the continuous model.

Both combinatory methods have the same deterministic rule for accepting the 'moves' (cold-swaps), which improve the cost function. However, the main difference between the Simulated Annealing and Tabu Search lies in the rule for accepting the hot-swaps which increase the cost function. The former applies a probabilistic approach and the latter uses a deterministic approach to accept the hot-swaps. In Simulated Annealing, the Metropolis Criterion probabilistically determines the acceptance of hot-swaps (discussed in Chapter 3) and the number of acceptances of hot-swaps diminishes in the subsequent steps with decreasing value of the initial control parameter at the specified cooling rate. In the case of the Tabu Search, the hot-swaps are deterministically accepted as long as the potential hot-swap drops below five percent of the swapping rate (discussed in Chapter 5). The number of hot-swaps determines the number of cold-swaps for the given swapping rate. In this hypothetical problem, the acceptance of hot-swaps dropped quickly and became zero at the sixth step at the swapping rate (S_R = 50*V_C) in the Simulated Annealing (see Figure 9.1). The number of cold-swaps also decreased at about the same rate in the Simulated Annealing and accepted a few cold-swaps per step until it became zero. In the Tabu Search, the acceptance of hot-swaps decreased gradually till the potential hot-swap acceptance dropped below five percent of the swapping rate at the 20th step. Due to the higher number of hot-swap acceptances in the Tabu Search, the cost function was not as much improved as in the Simulated Annealing. More improvement of the cost function took place after the hot-swaps became zero in the Tabu Search by accepting more than double the number of cold-swaps in the Simulated Annealing (see Figures 9.3 and 9.4). The difference in the number of hot-swaps and cold-swaps acceptances does not a make difference in the cost function improvement between the Simulated Annealing and Tabu Search. The Tabu Search accepted more than 10 times the number of cold-swaps and hot-swaps than the Simulated Annealing (see Figure 9.1) but minimized the cost function to about the same level (see Figure 9.2).

The more spatially compact land use allocation in Simulated Annealing for the same values of compactness factor could be attributed to the stopping rule used in these algorithms (see Table 9.5). In the case of Simulated Annealing, the algorithm stopped when the acceptance of cold-swaps became zero in an iteration step. Thus the algorithm with compactness function could accept more land use exchanges which increased spatial compactness. In Tabu Search, the algorithm terminated when the cost function did not change throughout an iteration step. This stopping criterion has the same implication as the stopping criterion used for the Simulated Annealing in optimising land use allocation without compactness function. However, the stopping rule of Tabu Search did not allow the algorithm to run if the cost function was higher than the previous iteration step. Therefore, the Tabu Search algorithm with compactness function terminated before the cold-swaps became zero and resulted lesser spatial compactness than the Simulated Annealing.

9.3 Conclusion

Both combinatory methods produced a solution superior to that reached by the MOLA module with minimum cost function, as well as a more spatially compact land use allocation for the same MOLAA problem. These combinatory methods are approximate optimisation methods and they produce a final solution with minimum cost function by searching for a land use for each land unit at the lowest cost. The MOLA module is a deterministic method and uses a fixed decision rule (discussed in Chapter 3) to allocate a land use to each land unit with the best rank value using the rank maps. However, the MOLA produces a solution with the same spatial pattern in different runs for the same data inputs (rank maps). It could neither maximize land use suitability nor the spatial compactness and as a result, produced a solution inferior to that reached by the combinatory methods.

However, the combinatory methods were not as efficient as the MOLA module in terms of the computation time taken to deliver a solution to a large grid MOLAA problem. These methods generate a solution that is close to a near-optimal solution in an acceptable computational time. Hence, the combinatory methods are found to be more appropriate in solving a MOLAA problem than the MOLA module, but computation time had to be compromised in order to reach a good solution.

Within the combinatory methods, the Simulated Annealing was found to be more efficient and effective than the Tabu Search in solving a MOLAA problem. The former method delivered a solution to MOLAA problems in all sizes with lower cost function in less computation time than the latter method.

9.4 Summary

This chapter presented a comparison of the MOLA module and the combinatory methods in solving the same MOLAA problem. The solutions obtained by applying these methods were compared by using the cost function, spatial compactness and the computation time. The cost function was more improved in the solution by the combinatory methods than that of the MOLA module. The spatial compactness measured in the number of patches was also found to be less in the land use allocation by the combinatory methods. However, the MOLA module was found to be computationally more efficient than the combinatory methods. Within the combinatory methods, the Simulated Annealing produced better solution than the Tabu Search in less computation time.

Chapter 10

CONCLUSIONS

The main aim of this research was to compare the performance of two combinatory methods and a GIS based MOLA module in solving a multi-objective land use assessment and allocation problem in order to provide an informed choice among these methods. Among the combinatory methods, Simulated Annealing and Tabu Search algorithms were chosen and their performances were compared with the MOLA module in IDRISI® by using the cost suitability values, spatial compactness and computation time to deliver the solution.

Decision makers/land use planners or consultants could apply these methods to solve multi-objective land use assessment and allocation (MOLAA) problems in regional land use planning that involves several stakeholders. The Multi-Criteria Evaluation (MCE) technique, the methodology used in this study, would enable the decision makers/land use planners or consultants to use the different socio-economic and environmental aims of the stakeholders to decide on multiple criteria for assessing the suitability of each land unit or land parcel for different land uses. These methods accomplish land use allocation by using aggregate land use suitability values derived by the Weighted Linear Combination method. These methods objectively produced a solution to the MOLAA problem based on the criteria and their preferences specified by the stakeholders. Therefore, the decision makers/land use planners or consultants will find these methods useful for reaching a consensus decision among stakeholders, using the land use allocation alternatives generated by these methods. The overall conclusions of this research regarding the application and comparisons of three different methods in solving a MOLAA problem are as follows:

This study demonstrated the application of two combinatory methods (Simulated Annealing and Tabu Search) in solving a MOLAA problem using land use cost suitability models generated by a Weighted Linear Combination of ordinal, continuous and fuzzy criteria maps.

For a land allocation problem, the solutions delivered by the MOLA module and the combinatory methods were found to be different due to the difference in the approaches and the different rules of land use allocation between these two methods. The MOLA module applies a deterministic approach whereas the combinatory methods are based on an iterative approach for assigning a land use to each land unit. Another difference is that the MOLA module uses the rank maps derived from the land use suitability maps but the combinatory methods use the same land use suitability modules, with the lowest values representing the highest relative suitability and the lowest relative suitability being represented by the highest values.

For the same MOLAA problem, the combinatory methods improved (minimized) the cost function in the final solution higher than in the solution generated by the MOLA module. The combinatory methods allocate each land unit with a land use that has the lowest cost suitability value and can generate a solution close to a near optimal solution to a MOLAA problem. In the case of the MOLA module, it ignores the relative suitability of various land uses for each land unit and assigns land use by taking into account the rank values. Hence, this module could not maximize land use suitability for a MOLAA problem and resulted a higher cost function.

Without taking into account the spatial compactness function in the algorithms, these combinatory methods could produce a land use allocation with overall higher spatial compactness than the solution by the MOLA module. However, the MOLA module could produce higher spatial compactness for those land uses with higher area requirements.

In the combinatory methods, users are able to see the difference between the initial and the final solution and the improvement in the land use allocation brought about by the algorithm. Therefore, decision makers/land use planners would be able to see the improvement in the land use allocation by comparing the initial and final solutions. In addition, these algorithms also provide an exact quantitative estimate of the cost function in the initial solution and the final solution and the saving in the cost between these two solutions in the output file. However, the MOLA module does not provide such a comparison and the quality of the solution could not be evaluated.

Both algorithms could produce more compact land use allocations by incorporating a compactness function in the algorithms. However, the MOLA module does not have this capability. The users could choose the compactness factor value to achieve a desired level of spatial compactness, but the value depends on the magnitude of values of the cost suitability models. The users could also apply a compactness function in Simulated Annealing and Tabu Search in order to achieve a better spatial compactness using appropriate compactness factor. This study found that Simulated Annealing produced a better spatial compactness than Tabu Search using the same values of compactness factor and cost model.

Users would find the MOLA module very efficient and justify their choice of applying this module to solving a MOLAA problem. In terms of the computation time taken by the combinatory methods to deliver a solution to the same problem, this group of methods was found to be less efficient compared to the MOLA module, however, they delivered a solution in an acceptable period of time.

The Simulated Annealing could produce a global solution with a very slow cooling rate and a high number of swaps in Mode 1 cooling function. However, a more appropriate annealing schedule was found to be more efficient and could produce a solution close to a near-optimal solution. The algorithm should be applied using an annealing schedule with a high value of initial control parameter, cooling by the very fast cooling rate (0.2) after a swapping rate of 100 times the number of valid cells in the grid for solving a MOLAA problem. In this annealing schedule, the cooling rate is fixed and the user can easily decide on the swapping rate after finding the number of valid cells in the grid. Regarding the initial control parameter value, they could apply the algorithm a few times in order to find an appropriate value of the control parameter for the input solution.

The user could also apply Tabu Search to a MOLAA problem simply by using only two parameters, that is, Tabu length and number of swaps per step (swapping step). The appropriate values of the Tabu length and swapping rate were found to be 10 and 50 times the number of valid cells in the grid, respectively. The higher value of Tabu length did not influence the cost function minimization and therefore, the appropriate value of the Tabu length was fixed at 10, the lowest value allowed in the programme. The users could easily find out the number of valid cells in the grid by excluding the mandatory land uses during preparing the input models. In contrast to Simulated

Annealing, Tabu Search uses a deterministic rule for accepting the hot-swaps and the users can easily understand the algorithmic process of the Tabu Search.

The land use allocation by these algorithms was influenced by the cost suitability models and the initial input solution in solving a MOLAA problem. The algorithms performed better in the model with a higher number of discrete values (representing land use suitability for different land uses, that is, the fuzzy model) than in the one with a lesser number of discrete values as in the continuous and ordinal models. The users might find the ordinal model simpler than the fuzzy model. However, the fuzzy model is less subjective than the ordinal model and requires only thresholds for suitable and unsuitable attribute classes for a criterion. The decision makers/land use planners or consultants may find it easier to arrive at a consensus about these thresholds values among the stakeholders by employing the fuzzy model.

These algorithms could produce even more improvement in the cost function by using the random initial input solution of the fuzzy cost model. The users could a find huge visual difference between the random initial input solution and the final solution and also notice a quantitative difference between the initial and final cost functions. The visual difference is not so noticeable between the cheapest or greatest difference initial input solution and the final solution.

In the comparison of two combinatory methods in terms of the quality of the solution, spatial compactness and computation time, the Simulated Annealing delivered a better quality solution with lesser cost function and higher spatial compactness in less computation time than that taken by Tabu Search for the same MOLAA problem. Thus, the users could obtain better decision alternatives to a land use allocation problem by applying Simulated Annealing with the recommended appropriate annealing schedule, using the random initial input solution of a fuzzy model.

Thus Simulated Annealing has been demonstrated to be a highly suitable tool for solving a large size MOLAA problem within a reasonable time frame. This algorithm should be integrated within the GIS environment with the user-friendly Graphic User Interface so that this tool is available to provide genuine support in land use decision-making.

This study considered two spatial attributes, that is, area and spatial compactness, in these algorithms. Future research should consider incorporating other desirable (spatial or non-spatial) attributes like a shape and adjacency requirement in the algorithm.

In the case of Tabu Search, the Tabu list with location attributes of the land units did not exert any influence on the cost function minimization. Future research should look at other attributes like cost value and land use in defining the Tabu list and evaluate their influence on the overall performance of the algorithm.

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Annex –1: An example of output summary from the Simulated Annealing

```
*** siman2d ***

Simulated annealing program
Version 1.10
written by Steve Leahy, SRES, ANU
April 2004
for Sunil Sharma


Running in mode 1 - hot and cold swaps

Initial temperature=15000.000000
Temperature reduction factor=0.200000
Minimum temperature =0.000000
Number of swaps per interation=18611800

Compactness factor=0

Will not output intermediate grids

Parsing header file:
      header file is:con525.hdr
Done

      Array width=525
      Array height=525
      Array size=275625

Loading input cost grid output_525or_C:
      float file is:output_525or_C.flt
Done

Loading input land use grid output_525or_LU:
      float file is:output_525or_LU.flt
Done

Loading land use class 0 array con525:
      float file is:con525.flt
Done

Loading land use class 1 array agri525:
      float file is:agri525.flt
Done

Loading land use class 2 array foro525:
      float file is:foro525.flt
Done

Loading land use class 3 array deve525:
      float file is:deve525.flt
Done

Number of noData points in grid: 89507

Number of valid points in grid: 186118

Initial total cost of grid=93526457

It: 1 Temp: 15000 Cold: 5980739 Hot: 5981880 Zero-nonswap:6529691 Tot:
93021561
It: 2 Temp: 3000 Cold: 5754102 Hot: 5750808 Zero-nonswap:6527723 Tot: 91436440
It: 3 Temp: 600 Cold: 4751168 Hot: 4738393 Zero-nonswap:6527456 Tot: 86555791
It: 4 Temp: 120 Cold: 1947371 Hot: 1904023 Zero-nonswap:6504173 Tot: 75072291
It: 5 Temp: 24 Cold: 302038 Hot: 238666 Zero-nonswap:6463286 Tot: 69022885
It: 6 Temp: 4.80 Cold: 43022 Hot: 16673 Zero-nonswap:6440850 Tot: 68348674
It: 7 Temp: 0.960 Cold: 6357 Hot: 1096 Zero-nonswap:6436630 Tot: 68303400
It: 8 Temp: 0.1920000166 Cold: 1618 Hot: 17 Zero-nonswap:6431796 Tot: 68294447
It: 9 Temp: 0.0384000055 Cold: 652 Hot: 0 Zero-nonswap:6430331 Tot: 68291008
It: 10 Temp: 0.0076800012 Cold: 382 Hot: 0 Zero-nonswap:6430501 Tot: 68289192
It: 11 Temp: 0.0015360003 Cold: 206 Hot: 0 Zero-nonswap:6433715 Tot: 68288221
It: 12 Temp: 0.0003072001 Cold: 150 Hot: 0 Zero-nonswap:6432339 Tot: 68287578
It: 13 Temp: 0.0000614400 Cold: 107 Hot: 0 Zero-nonswap:6431188 Tot: 68287189
It: 14 Temp: 0.0000122880 Cold: 86 Hot: 0 Zero-nonswap:6432413 Tot: 68286897
```

```
It: 15 Temp: 0.0000024576 Cold: 60 Hot: 0 Zero-nonswap:6430404 Tot: 68286711
It: 16 Temp: 0.0000004915 Cold: 49 Hot: 0 Zero-nonswap:6432915 Tot: 68286548
It: 17 Temp: 0.0000000983 Cold: 44 Hot: 0 Zero-nonswap:6432483 Tot: 68286413
It: 18 Temp: 0.0000000197 Cold: 25 Hot: 0 Zero-nonswap:6433538 Tot: 68286347
It: 19 Temp: 0.0000000039 Cold: 24 Hot: 0 Zero-nonswap:6433055 Tot: 68286279
It: 20 Temp: 0.0000000008 Cold: 26 Hot: 0 Zero-nonswap:6429741 Tot: 68286221
It: 21 Temp: 0.0000000002 Cold: 22 Hot: 0 Zero-nonswap:6430273 Tot: 68286134
It: 22 Temp: 0.0000000000 Cold: 16 Hot: 0 Zero-nonswap:6430421 Tot: 68286099
It: 23 Temp: 0.0000000000 Cold: 9 Hot: 0 Zero-nonswap:6435530 Tot: 68286070
It: 24 Temp: 0.0000000000 Cold: 11 Hot: 0 Zero-nonswap:6433965 Tot: 68286042
It: 25 Temp: 0.0000000000 Cold: 7 Hot: 0 Zero-nonswap:6431622 Tot: 68286026
It: 26 Temp: 0.0000000000 Cold: 8 Hot: 0 Zero-nonswap:6432330 Tot: 68286000
It: 27 Temp: 0.0000000000 Cold: 3 Hot: 0 Zero-nonswap:6431168 Tot: 68285994
It: 28 Temp: 0.0000000000 Cold: 11 Hot: 0 Zero-nonswap:6429728 Tot: 68285975
It: 29 Temp: 0.0000000000 Cold: 9 Hot: 0 Zero-nonswap:6432997 Tot: 68285952
It: 30 Temp: 0.0000000000 Cold: 3 Hot: 0 Zero-nonswap:6429348 Tot: 68285944
It: 31 Temp: 0.0000000000 Cold: 6 Hot: 0 Zero-nonswap:6430547 Tot: 68285928
It: 32 Temp: 0.0000000000 Cold: 4 Hot: 0 Zero-nonswap:6431729 Tot: 68285921
It: 33 Temp: 0.0000000000 Cold: 7 Hot: 0 Zero-nonswap:6431016 Tot: 68285913
It: 34 Temp: 0.0000000000 Cold: 4 Hot: 0 Zero-nonswap:6432582 Tot: 68285907
It: 35 Temp: 0.0000000000 Cold: 2 Hot: 0 Zero-nonswap:6429832 Tot: 68285903
It: 36 Temp: 0.0000000000 Cold: 3 Hot: 0 Zero-nonswap:6431301 Tot: 68285897
It: 37 Temp: 0.0000000000 Cold: 4 Hot: 0 Zero-nonswap:6429479 Tot: 68285889
It: 38 Temp: 0.0000000000 Cold: 6 Hot: 0 Zero-nonswap:6432274 Tot: 68285882
It: 39 Temp: 0.0000000000 Cold: 4 Hot: 0 Zero-nonswap:6432173 Tot: 68285876
It: 40 Temp: 0.0000000000 Cold: 1 Hot: 0 Zero-nonswap:6431526 Tot: 68285875
It: 41 Temp: 0.0000000000 Cold: 1 Hot: 0 Zero-nonswap:6430129 Tot: 68285870
It: 42 Temp: 0.0000000000 Cold: 2 Hot: 0 Zero-nonswap:6434556 Tot: 68285866
It: 43 Temp: 0.0000000000 Cold: 4 Hot: 0 Zero-nonswap:6434974 Tot: 68285861
It: 44 Temp: 0.0000000000 Cold: 1 Hot: 0 Zero-nonswap:6431706 Tot: 68285859
It: 45 Temp: 0.0000000000 Cold: 1 Hot: 0 Zero-nonswap:6431526 Tot: 68285858
It: 46 Temp: 0.0000000000 Cold: 4 Hot: 0 Zero-nonswap:6433345 Tot: 68285853
It: 47 Temp: 0.0000000000 Cold: 1 Hot: 0 Zero-nonswap:6430469 Tot: 68285852
It: 48 Temp: 0.0000000000 Cold: 4 Hot: 0 Zero-nonswap:6431848 Tot: 68285844
It: 49 Temp: 0.0000000000 Cold: 1 Hot: 0 Zero-nonswap:6429670 Tot: 68285843
It: 50 Temp: 0.0000000000 Cold: 3 Hot: 0 Zero-nonswap:6432848 Tot: 68285837
It: 51 Temp: 0.0000000000 Cold: 0 Hot: 0 Zero-nonswap:6431567 Tot: 68285837

Number of temperature interations=51

Original total cost=93526457
New total cost=68285837
Saving=25240620

Writing final output land use grid output_525or_final_LU to disc:Done

Writing final output cost grid output_525or_final_C to disc:Done


*** end simulated annealing ***
```

Annex – 2: An example of output summary from the Tabu Search

```
*** taboo.exe ***

written by Steve Leahy, SRES, ANU
January 2005
for Sunil Sharma

Running in mode 1 - static number of swaps per iteration

Number of comparisons per cell=1

Static number of swaps per interation=9305900

Compactness factor=0

Will not output intermediate grids

Parsing header file:
        header file is:con525o.hdr
Done

        Array width=525
        Array height=525
        Array size=275625

Taboo list length=10

Loading input cost grid output_525or_C:
        float file is:output_525or_C.flt
Done

Loading input land use grid output_525or_LU:
        float file is:output_525or_LU.flt
Done

Loading land use class 0 array con525o:
        float file is:con525o.flt
Done

Loading land use class 1 array agri525o:
        float file is:agri525o.flt
Done

Loading land use class 2 array foro525o:
        float file is:foro525o.flt
Done

Loading land use class 3 array deve525o:
        float file is:deve525o.flt
Done

cross-validating input grids:done

Number of noData points in grid: 89507

Number of valid points in grid: 186118

Initial total cost of grid=93526457

Iteration: 1  Pot. swaps: 9305900  act. swaps: 9224953 pot. hot swaps 9305900
        cold swaps: 4612830 hot swaps: 4612123 Total cost: 93500043
Iteration: 2  Pot. swaps: 9305900  act. swaps: 9224782 pot. hot swaps 4652950
        cold swaps: 4611939 hot swaps: 4612843 Total cost: 93545398
Iteration: 3  Pot. swaps: 9305900  act. swaps: 6380053 pot. hot swaps 3101966
        cold swaps: 3278087 hot swaps: 3101966 Total cost: 68817117
Iteration: 4  Pot. swaps: 9305900  act. swaps: 4783648 pot. hot swaps 2326475
        cold swaps: 2457173 hot swaps: 2326475 Total cost: 68573265
Iteration: 5  Pot. swaps: 9305900  act. swaps: 3856211 pot. hot swaps 1861180
        cold swaps: 1995031 hot swaps: 1861180 Total cost: 68506184
Iteration: 6  Pot. swaps: 9305900  act. swaps: 3237298 pot. hot swaps 1550983
        cold swaps: 1686315 hot swaps: 1550983 Total cost: 68469973
Iteration: 7  Pot. swaps: 9305900  act. swaps: 2796854 pot. hot swaps 1329414
        cold swaps: 1467440 hot swaps: 1329414 Total cost: 68450670
Iteration: 8  Pot. swaps: 9305900  act. swaps: 2463367 pot. hot swaps 1163237
        cold swaps: 1300130 hot swaps: 1163237 Total cost: 68439314
Iteration: 9  Pot. swaps: 9305900  act. swaps: 2204661 pot. hot swaps 1033988
```

```
       cold swaps: 1170673 hot swaps: 1033988 Total cost: 68427795
Iteration: 10  Pot. swaps: 9305900  act. swaps: 1998198 pot. hot swaps 930590
       cold swaps: 1067608 hot swaps: 930590 Total cost: 68418439
Iteration: 11  Pot. swaps: 9305900  act. swaps: 1829234 pot. hot swaps 845990
       cold swaps: 983244 hot swaps: 845990 Total cost: 68413784
Iteration: 12  Pot. swaps: 9305900  act. swaps: 1689664 pot. hot swaps 775491
       cold swaps: 914173 hot swaps: 775491 Total cost: 68411632
Iteration: 13  Pot. swaps: 9305900  act. swaps: 1568540 pot. hot swaps 715838
       cold swaps: 852702 hot swaps: 715838 Total cost: 68410793
Iteration: 14  Pot. swaps: 9305900  act. swaps: 1468002 pot. hot swaps 664707
       cold swaps: 803295 hot swaps: 664707 Total cost: 68407513
Iteration: 15  Pot. swaps: 9305900  act. swaps: 1379296 pot. hot swaps 620393
       cold swaps: 758903 hot swaps: 620393 Total cost: 68402689
Iteration: 16  Pot. swaps: 9305900  act. swaps: 1301323 pot. hot swaps 581618
       cold swaps: 719705 hot swaps: 581618 Total cost: 68403573
Iteration: 17  Pot. swaps: 9305900  act. swaps: 1234357 pot. hot swaps 547405
       cold swaps: 686952 hot swaps: 547405 Total cost: 68402724
Iteration: 18  Pot. swaps: 9305900  act. swaps: 1173003 pot. hot swaps 516994
       cold swaps: 656009 hot swaps: 516994 Total cost: 68397715
Iteration: 19  Pot. swaps: 9305900  act. swaps: 1119254 pot. hot swaps 489784
       cold swaps: 629470 hot swaps: 489784 Total cost: 68396601
Iteration: 20  Pot. swaps: 9305900  act. swaps: 1070266 pot. hot swaps 465295
       cold swaps: 604971 hot swaps: 465295 Total cost: 68402478
Iteration: 21  Pot. swaps: 9305900  act. swaps: 6884 pot. hot swaps 0
       cold swaps: 6884 hot swaps: 0 Total cost: 68320898
Iteration: 22  Pot. swaps: 9305900  act. swaps: 2135 pot. hot swaps 0
       cold swaps: 2135 hot swaps: 0 Total cost: 68303661
Iteration: 23  Pot. swaps: 9305900  act. swaps: 1049 pot. hot swaps 0
       cold swaps: 1049 hot swaps: 0 Total cost: 68296833
Iteration: 24  Pot. swaps: 9305900  act. swaps: 600 pot. hot swaps 0
       cold swaps: 600 hot swaps: 0 Total cost: 68293446
Iteration: 25  Pot. swaps: 9305900  act. swaps: 379 pot. hot swaps 0
       cold swaps: 379 hot swaps: 0 Total cost: 68291567
Iteration: 26  Pot. swaps: 9305900  act. swaps: 266 pot. hot swaps 0
       cold swaps: 266 hot swaps: 0 Total cost: 68290347
Iteration: 27  Pot. swaps: 9305900  act. swaps: 204 pot. hot swaps 0
       cold swaps: 204 hot swaps: 0 Total cost: 68289490
Iteration: 28  Pot. swaps: 9305900  act. swaps: 149 pot. hot swaps 0
       cold swaps: 149 hot swaps: 0 Total cost: 68288866
Iteration: 29  Pot. swaps: 9305900  act. swaps: 105 pot. hot swaps 0
       cold swaps: 105 hot swaps: 0 Total cost: 68288464
Iteration: 30  Pot. swaps: 9305900  act. swaps: 101 pot. hot swaps 0
       cold swaps: 101 hot swaps: 0 Total cost: 68288148
Iteration: 31  Pot. swaps: 9305900  act. swaps: 65 pot. hot swaps 0
       cold swaps: 65 hot swaps: 0 Total cost: 68287930
Iteration: 32  Pot. swaps: 9305900  act. swaps: 59 pot. hot swaps 0
       cold swaps: 59 hot swaps: 0 Total cost: 68287748
Iteration: 33  Pot. swaps: 9305900  act. swaps: 54 pot. hot swaps 0
       cold swaps: 54 hot swaps: 0 Total cost: 68287591
Iteration: 34  Pot. swaps: 9305900  act. swaps: 41 pot. hot swaps 0
       cold swaps: 41 hot swaps: 0 Total cost: 68287474
Iteration: 35  Pot. swaps: 9305900  act. swaps: 35 pot. hot swaps 0
       cold swaps: 35 hot swaps: 0 Total cost: 68287352
Iteration: 36  Pot. swaps: 9305900  act. swaps: 24 pot. hot swaps 0
       cold swaps: 24 hot swaps: 0 Total cost: 68287266
Iteration: 37  Pot. swaps: 9305900  act. swaps: 32 pot. hot swaps 0
       cold swaps: 32 hot swaps: 0 Total cost: 68287162
Iteration: 38  Pot. swaps: 9305900  act. swaps: 28 pot. hot swaps 0
       cold swaps: 28 hot swaps: 0 Total cost: 68287078
Iteration: 39  Pot. swaps: 9305900  act. swaps: 26 pot. hot swaps 0
       cold swaps: 26 hot swaps: 0 Total cost: 68287004
Iteration: 40  Pot. swaps: 9305900  act. swaps: 18 pot. hot swaps 0
       cold swaps: 18 hot swaps: 0 Total cost: 68286955
Iteration: 41  Pot. swaps: 9305900  act. swaps: 15 pot. hot swaps 0
       cold swaps: 15 hot swaps: 0 Total cost: 68286914
Iteration: 42  Pot. swaps: 9305900  act. swaps: 8 pot. hot swaps 0
       cold swaps: 8 hot swaps: 0 Total cost: 68286886
Iteration: 43  Pot. swaps: 9305900  act. swaps: 9 pot. hot swaps 0
       cold swaps: 9 hot swaps: 0 Total cost: 68286866
Iteration: 44  Pot. swaps: 9305900  act. swaps: 10 pot. hot swaps 0
       cold swaps: 10 hot swaps: 0 Total cost: 68286836
Iteration: 45  Pot. swaps: 9305900  act. swaps: 11 pot. hot swaps 0
       cold swaps: 11 hot swaps: 0 Total cost: 68286818
Iteration: 46  Pot. swaps: 9305900  act. swaps: 6 pot. hot swaps 0
       cold swaps: 6 hot swaps: 0 Total cost: 68286807
Iteration: 47  Pot. swaps: 9305900  act. swaps: 13 pot. hot swaps 0
       cold swaps: 13 hot swaps: 0 Total cost: 68286781
Iteration: 48  Pot. swaps: 9305900  act. swaps: 11 pot. hot swaps 0
       cold swaps: 11 hot swaps: 0 Total cost: 68286756
Iteration: 49  Pot. swaps: 9305900  act. swaps: 6 pot. hot swaps 0
```

```
       cold swaps: 6 hot swaps: 0 Total cost: 68286744
Iteration: 50  Pot. swaps: 9305900  act. swaps: 6 pot. hot swaps 0
       cold swaps: 6 hot swaps: 0 Total cost: 68286730
Iteration: 51  Pot. swaps: 9305900  act. swaps: 5 pot. hot swaps 0
       cold swaps: 5 hot swaps: 0 Total cost: 68286720
Iteration: 52  Pot. swaps: 9305900  act. swaps: 5 pot. hot swaps 0
       cold swaps: 5 hot swaps: 0 Total cost: 68286711
Iteration: 53  Pot. swaps: 9305900  act. swaps: 3 pot. hot swaps 0
       cold swaps: 3 hot swaps: 0 Total cost: 68286708
Iteration: 54  Pot. swaps: 9305900  act. swaps: 10 pot. hot swaps 0
       cold swaps: 10 hot swaps: 0 Total cost: 68286690
Iteration: 55  Pot. swaps: 9305900  act. swaps: 4 pot. hot swaps 0
       cold swaps: 4 hot swaps: 0 Total cost: 68286680
Iteration: 56  Pot. swaps: 9305900  act. swaps: 6 pot. hot swaps 0
       cold swaps: 6 hot swaps: 0 Total cost: 68286672
Iteration: 57  Pot. swaps: 9305900  act. swaps: 6 pot. hot swaps 0
       cold swaps: 6 hot swaps: 0 Total cost: 68286661
Iteration: 58  Pot. swaps: 9305900  act. swaps: 7 pot. hot swaps 0
       cold swaps: 7 hot swaps: 0 Total cost: 68286645
Iteration: 59  Pot. swaps: 9305900  act. swaps: 4 pot. hot swaps 0
       cold swaps: 4 hot swaps: 0 Total cost: 68286634
Iteration: 60  Pot. swaps: 9305900  act. swaps: 4 pot. hot swaps 0
       cold swaps: 4 hot swaps: 0 Total cost: 68286624
Iteration: 61  Pot. swaps: 9305900  act. swaps: 4 pot. hot swaps 0
       cold swaps: 4 hot swaps: 0 Total cost: 68286611
Iteration: 62  Pot. swaps: 9305900  act. swaps: 6 pot. hot swaps 0
       cold swaps: 6 hot swaps: 0 Total cost: 68286595
Iteration: 63  Pot. swaps: 9305900  act. swaps: 5 pot. hot swaps 0
       cold swaps: 5 hot swaps: 0 Total cost: 68286579
Iteration: 64  Pot. swaps: 9305900  act. swaps: 3 pot. hot swaps 0
       cold swaps: 3 hot swaps: 0 Total cost: 68286572
Iteration: 65  Pot. swaps: 9305900  act. swaps: 1 pot. hot swaps 0
       cold swaps: 1 hot swaps: 0 Total cost: 68286571
Iteration: 66  Pot. swaps: 9305900  act. swaps: 2 pot. hot swaps 0
       cold swaps: 2 hot swaps: 0 Total cost: 68286567
Iteration: 67  Pot. swaps: 9305900  act. swaps: 3 pot. hot swaps 0
       cold swaps: 3 hot swaps: 0 Total cost: 68286558
Iteration: 68  Pot. swaps: 9305900  act. swaps: 1 pot. hot swaps 0
       cold swaps: 1 hot swaps: 0 Total cost: 68286556
Iteration: 69  Pot. swaps: 9305900  act. swaps: 2 pot. hot swaps 0
       cold swaps: 2 hot swaps: 0 Total cost: 68286552
Iteration: 70  Pot. swaps: 9305900  act. swaps: 3 pot. hot swaps 0
       cold swaps: 3 hot swaps: 0 Total cost: 68286546
Iteration: 71  Pot. swaps: 9305900  act. swaps: 2 pot. hot swaps 0
       cold swaps: 2 hot swaps: 0 Total cost: 68286540
Iteration: 72  Pot. swaps: 9305900  act. swaps: 3 pot. hot swaps 0
       cold swaps: 3 hot swaps: 0 Total cost: 68286533
Iteration: 73  Pot. swaps: 9305900  act. swaps: 4 pot. hot swaps 0
       cold swaps: 4 hot swaps: 0 Total cost: 68286525
Iteration: 74  Pot. swaps: 9305900  act. swaps: 1 pot. hot swaps 0
       cold swaps: 1 hot swaps: 0 Total cost: 68286522
Iteration: 75  Pot. swaps: 9305900  act. swaps: 1 pot. hot swaps 0
       cold swaps: 1 hot swaps: 0 Total cost: 68286521
Iteration: 76  Pot. swaps: 9305900  act. swaps: 1 pot. hot swaps 0
       cold swaps: 1 hot swaps: 0 Total cost: 68286518
Iteration: 77  Pot. swaps: 9305900  act. swaps: 1 pot. hot swaps 0
       cold swaps: 1 hot swaps: 0 Total cost: 68286517
Iteration: 78  Pot. swaps: 9305900  act. swaps: 2 pot. hot swaps 0
       cold swaps: 2 hot swaps: 0 Total cost: 68286515
Iteration: 79  Pot. swaps: 9305900  act. swaps: 2 pot. hot swaps 0
       cold swaps: 2 hot swaps: 0 Total cost: 68286512
Iteration: 80  Pot. swaps: 9305900  act. swaps: 1 pot. hot swaps 0
       cold swaps: 1 hot swaps: 0 Total cost: 68286510
Iteration: 81  Pot. swaps: 9305900  act. swaps: 0 pot. hot swaps 0
       cold swaps: 0 hot swaps: 0 Total cost: 68286510

Number of interations=81

Original total cost=93526457
New total cost=68286510

Saving=25239947

Writing final output land use grid output_525or_final_LU to disc:Done

Writing final output cost grid output_525or_final_C to disc:Done


*** end Tabu Search***
```

Annex – 3: An example of output file from the MOLA module

```
Area desired for objective 1 : 93059 cells
Area desired for objective 2 : 46530 cells
Area desired for objective 3 : 27918 cells
Area desired for objective 4 : 18611 cells
Area tolerance : : 0 cells
Results from Pass 1 :
Objective : 1     Cut : 93059     Goal : 93059     Achieved : 67441
Objective : 2     Cut : 46530     Goal : 46530     Achieved : 33367
Objective : 3     Cut : 27918     Goal : 27918     Achieved : 22228
Objective : 4     Cut : 18611     Goal : 18611     Achieved : 12051
Results from Pass 2 :
Objective : 1     Cut : 128408     Goal : 93059     Achieved : 82070
Objective : 2     Cut : 64886     Goal : 46530     Achieved : 41093
Objective : 3     Cut : 35065     Goal : 27918     Achieved : 27107
Objective : 4     Cut : 28742     Goal : 18611     Achieved : 16575
Results from Pass 3 :
Objective : 1     Cut : 140868     Goal : 93059     Achieved : 83432
Objective : 2     Cut : 71042     Goal : 46530     Achieved : 43607
Objective : 3     Cut : 35900     Goal : 27918     Achieved : 27680
Objective : 4     Cut : 31028     Goal : 18611     Achieved : 17835
Results from Pass 4 :
Objective : 1     Cut : 151606     Goal : 93059     Achieved : 85341
Objective : 2     Cut : 74161     Goal : 46530     Achieved : 44595
Objective : 3     Cut : 36140     Goal : 27918     Achieved : 27853
Objective : 4     Cut : 31838     Goal : 18611     Achieved : 17985
Results from Pass 5 :
Objective : 1     Cut : 160022     Goal : 93059     Achieved : 87695
Objective : 2     Cut : 76180     Goal : 46530     Achieved : 45215
Objective : 3     Cut : 36205     Goal : 27918     Achieved : 27891
Objective : 4     Cut : 32486     Goal : 18611     Achieved : 18101
Results from Pass 6 :
Objective : 1     Cut : 165714     Goal : 93059     Achieved : 88888
Objective : 2     Cut : 77533     Goal : 46530     Achieved : 45596
Objective : 3     Cut : 36232     Goal : 27918     Achieved : 27908
Objective : 4     Cut : 33010     Goal : 18611     Achieved : 18267
Results from Pass 7 :
Objective : 1     Cut : 170081     Goal : 93059     Achieved : 89715
Objective : 2     Cut : 78486     Goal : 46530     Achieved : 45871
Objective : 3     Cut : 36242     Goal : 27918     Achieved : 27914
Objective : 4     Cut : 33360     Goal : 18611     Achieved : 18372
Results from Pass 8 :
Objective : 1     Cut : 173550     Goal : 93059     Achieved : 90368
Objective : 2     Cut : 79154     Goal : 46530     Achieved : 45978
Objective : 3     Cut : 36246     Goal : 27918     Achieved : 27917
Objective : 4     Cut : 33602     Goal : 18611     Achieved : 18559
Results from Pass 9 :
Objective : 1     Cut : 176321     Goal : 93059     Achieved : 90869
Objective : 2     Cut : 79713     Goal : 46530     Achieved : 46134
Objective : 3     Cut : 36247     Goal : 27918     Achieved : 27918
Objective : 4     Cut : 33654     Goal : 18611     Achieved : 18605
Results from Pass 10 :
Objective : 1     Cut : 178564     Goal : 93059     Achieved : 91326
Objective : 2     Cut : 80112     Goal : 46530     Achieved : 46244
Objective : 3     Cut : 36247     Goal : 27918     Achieved : 27918
Objective : 4     Cut : 33660     Goal : 18611     Achieved : 18610
Results from Pass 11 :
Objective : 1     Cut : 180330     Goal : 93059     Achieved : 91710
Objective : 2     Cut : 80400     Goal : 46530     Achieved : 46340
Objective : 3     Cut : 36247     Goal : 27918     Achieved : 27918
Objective : 4     Cut : 33661     Goal : 18611     Achieved : 18610
Results from Pass 12 :
Objective : 1     Cut : 181699     Goal : 93059     Achieved : 91973
Objective : 2     Cut : 80591     Goal : 46530     Achieved : 46408
Objective : 3     Cut : 36247     Goal : 27918     Achieved : 27918
Objective : 4     Cut : 33662     Goal : 18611     Achieved : 18610
Results from Pass 13 :
Objective : 1     Cut : 182798     Goal : 93059     Achieved : 92243
Objective : 2     Cut : 80713     Goal : 46530     Achieved : 46439
Objective : 3     Cut : 36247     Goal : 27918     Achieved : 27918
Objective : 4     Cut : 33663     Goal : 18611     Achieved : 18611
Results from Pass 14 :
Objective : 1     Cut : 183621     Goal : 93059     Achieved : 92434
Objective : 2     Cut : 80804     Goal : 46530     Achieved : 46466
Objective : 3     Cut : 36247     Goal : 27918     Achieved : 27918
Objective : 4     Cut : 33663     Goal : 18611     Achieved : 18611
Results from Pass 15 :
Objective : 1     Cut : 184250     Goal : 93059     Achieved : 92586
```

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Objective : 2    Cut : 80868    Goal : 46530    Achieved : 46491
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 16 :
Objective : 1    Cut : 184725    Goal : 93059    Achieved : 92691
Objective : 2    Cut : 80907    Goal : 46530    Achieved : 46504
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 17 :
Objective : 1    Cut : 185094    Goal : 93059    Achieved : 92783
Objective : 2    Cut : 80933    Goal : 46530    Achieved : 46516
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 18 :
Objective : 1    Cut : 185371    Goal : 93059    Achieved : 92861
Objective : 2    Cut : 80947    Goal : 46530    Achieved : 46522
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 19 :
Objective : 1    Cut : 185569    Goal : 93059    Achieved : 92909
Objective : 2    Cut : 80955    Goal : 46530    Achieved : 46524
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 20 :
Objective : 1    Cut : 185719    Goal : 93059    Achieved : 92953
Objective : 2    Cut : 80961    Goal : 46530    Achieved : 46525
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 21 :
Objective : 1    Cut : 185825    Goal : 93059    Achieved : 92987
Objective : 2    Cut : 80966    Goal : 46530    Achieved : 46525
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 22 :
Objective : 1    Cut : 185897    Goal : 93059    Achieved : 92999
Objective : 2    Cut : 80971    Goal : 46530    Achieved : 46525
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 23 :
Objective : 1    Cut : 185957    Goal : 93059    Achieved : 93013
Objective : 2    Cut : 80976    Goal : 46530    Achieved : 46526
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 24 :
Objective : 1    Cut : 186003    Goal : 93059    Achieved : 93026
Objective : 2    Cut : 80980    Goal : 46530    Achieved : 46526
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 25 :
Objective : 1    Cut : 186036    Goal : 93059    Achieved : 93038
Objective : 2    Cut : 80984    Goal : 46530    Achieved : 46526
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 26 :
Objective : 1    Cut : 186057    Goal : 93059    Achieved : 93042
Objective : 2    Cut : 80988    Goal : 46530    Achieved : 46526
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 27 :
Objective : 1    Cut : 186074    Goal : 93059    Achieved : 93045
Objective : 2    Cut : 80992    Goal : 46530    Achieved : 46529
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 28 :
Objective : 1    Cut : 186088    Goal : 93059    Achieved : 93048
Objective : 2    Cut : 80993    Goal : 46530    Achieved : 46529
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 29 :
Objective : 1    Cut : 186099    Goal : 93059    Achieved : 93050
Objective : 2    Cut : 80994    Goal : 46530    Achieved : 46529
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 30 :
Objective : 1    Cut : 186108    Goal : 93059    Achieved : 93053
Objective : 2    Cut : 80995    Goal : 46530    Achieved : 46529
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 31 :
Objective : 1    Cut : 186114    Goal : 93059    Achieved : 93057
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Objective : 2    Cut : 80996    Goal : 46530    Achieved : 46529
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 32 :
Objective : 1    Cut : 186116    Goal : 93059    Achieved : 93059
Objective : 2    Cut : 80997    Goal : 46530    Achieved : 46529
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 33 :
Objective : 1    Cut : 186116    Goal : 93059    Achieved : 93059
Objective : 2    Cut : 80998    Goal : 46530    Achieved : 46529
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 34 :
Objective : 1    Cut : 186116    Goal : 93059    Achieved : 93059
Objective : 2    Cut : 80999    Goal : 46530    Achieved : 46529
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 35 :
Objective : 1    Cut : 186116    Goal : 93059    Achieved : 93059
Objective : 2    Cut : 81000    Goal : 46530    Achieved : 46529
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 36 :
Objective : 1    Cut : 186116    Goal : 93059    Achieved : 93058
Objective : 2    Cut : 81001    Goal : 46530    Achieved : 46530
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 37 :
Objective : 1    Cut : 186117    Goal : 93059    Achieved : 93058
Objective : 2    Cut : 81001    Goal : 46530    Achieved : 46530
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
Results from Pass 38 :
Objective : 1    Cut : 186118    Goal : 93059    Achieved : 93059
Objective : 2    Cut : 81001    Goal : 46530    Achieved : 46530
Objective : 3    Cut : 36247    Goal : 27918    Achieved : 27918
Objective : 4    Cut : 33663    Goal : 18611    Achieved : 18611
```

Annex – 4: Spatial compactness in the continuous and fuzzy cost models

Spatial compactness after applying compactness function in the medium grid of continuous model

Compactness Factor (F_C)	Random			Greatest		
	Cost function	R_T *h:m*	N_p	*Cost function*	R_T *h:m*	N_p
25	7567741	0:05	86	7569272	0:05	94
50	7624515	0:08	67	7626665	0:05	65
100	7731711	0:10	44	7718051	0:10	45
200	7734468	0:10	48	7848417	0:10	35

B. Spatial compactness after applying compactness function in the medium grid of fuzzy model

Compactness Factor (F_C)	Random			Greatest		
	Cost function	R_T *h:m*	N_p	*Cost function*	R_T *h:m*	N_p
25	29653547	0:05	135	29649719	0:03	132
50	29715049	0:06	104	29709458	0:06	105
100	29830131	0:06	92	29829212	0:06	94
200	30022380	0:08	75	30023073	0:06	85

C. Spatial compactness after applying compactness function in the large grid of continuous model

Compactness Factor (F_C)	Random			Greatest		
	Cost function	R_T *h:m*	N_p	*Cost function*	R_T *h:m*	N_p
25	130913116	4:12	863	130903364	4:12	890
50	132006416	4:11	546	132058112	4:11	548
100	133579466	4:12	416	133629267	4:12	449
200	133499573	4:12	444	135069677	4:11	324

D. Spatial compactness after applying compactness function in the large grid of fuzzy model

Compactness Factor (F_C)	Random			Greatest		
	Cost function	R_T *h:m*	N_p	*Cost function*	R_T *h:m*	N_p
25	451927103	4:15	1941	451932116	4:14	1920
50	453121323	4:14	1450	453116855	4:15	1426
100	456034863	4:14	992	456172030	4:15	940
200	460993790	4:15	605	460958519	4:15	615