Review of Mathematical Programming for Coastal Land Use Optimization

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1. Introduction

Conflicts over coastal land use (CLU) due to competing utilization of scarce resources along the coast line, which often create externalities[1] is a challenge to decision-makers (DMs). The decision issue is how to allocate coastal lands and relevant resources in appropriate direction. There are a number of questions pertaining to the issue: which types of land can be used, how much to utilize of each one, for which activities at given amount of resources, as well as the conditions of uses within particular circumstances. These questions are economic problems rather than technical ones, that is, there are alternative ways of use to be traded-off with the "best" alternative to be implemented. The "best" is the optimum, which is based on a number of desirable criteria with given restrictions. In practical terms, this allocation problem involves not only economic but also non-economic factors, e.g. physical characteristics, social preferences, policies and management schemes. Dealing with a complex ecosystem and the interactions of uses and consequences makes CLU allocation problem more complicated than other common land use problems.

Mathematical programming (MP) is suggested as a useful methodology to solve the allocation problem, especially when many decision variables, constraints and parameters are considered simultaneously. It can perform as a *model* to represent the abstraction of the real situation in a mathematical form. As a *programming* tool, it can be used to resolve conflict problem based on optimality criterion through a formalized set of instructions. These capabilities of MP enable it to provide the best option.

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1 Externalities are uncompensated losses or gains imposed on second parties caused by production or consumption activities in the economy. It implies that the impacts from coastal land use activities, in general, land degradation and pollutions borne by society, are "externalities" which, in theory, are the sources of the conflicts among land users. Due to market failure they are not internalized into the costs of producing market goods and services of each entrepreneur. They therefore lead to the misallocation of resources by the overexploitation of resources for short-term gains. Similar to the non-existence of a market, the absence of a well-accounted value of environmental goods and functions provided by coastal resources would cause a bias towards overexploitation or conversion of these resources to alternative options (AgÜero and Flores, 1996).

This paper aims to explore the potential of applying MP to CLU allocation problems. It includes a review of basic theoretical and methodological aspects as well as the application frameworks. The review of MP applied to natural resource problems in common cases also gives a broader idea of the scope of its application in CLU. The development of the technique enhances the performance of MP application especially in the fields of land and other natural resources utilization. The review of these relevant applications is therefore included. Additionally, the integration of geographical information system (GIS) with MP is an area of methodological interest.

This review however is limited to some selected MP methods, i.e. single-criterion approach—linear programming (LP) method and multi-criteria approach—goal programming (GP) and multi-objective programming (MOP) method. The advantages and disadvantages of the methods and frameworks, which result in different model formulations and solutions, are also discussed.

2. Theoretical and Methodological Background

The general form of MP problem comprises maximized or minimized objective function, f(x), which is a function of decision variable set x subject to a set of constraints g(x). The constraints require that g(x) set must belong to s_1 and the decision variables must fall into s_2.

$$
\begin{array}{ll}
\text{Optimize} & f(x) \\
\text{subject to} & g(x) \in s_1 \\
 & x \in s_2
\end{array}
$$

The optimum solution is reached by trading-off amongst various alternatives. Theoretically, the most efficient choice must be chosen, mentioned as Pareto optimality, i.e. no similar or better solution can be made without degrading others. The optimum solution can be obtained numerically via a trial-and-error approach called numerical method or via a set of logical and mathematical operations performed in a specific sequence called algorithm.[2]

Three common usages of MP are described by McCarl and Spreen (1997). They as follows:

1. MP model construction provides *insight* to the DMs in order to understand the problem interacting with the real situation thoroughly. It should be noted that the problem insight is non-numerical usage. In the same context, Dykstra (1984) emphasizes that in fact the DMs are seldom interested in numerical solutions but rather need information to base decisions in allocating and manipulating scarce resources in efficient direction.

2. The application of MP commonly involves the *solution prescription* which is most often used to predict the consequences of actions. In other words, MP model gives a practical solution for decision guidance but it is not always one that should be implemented.

3. The direct use of numerical solution is common in *technical aspects* such as sensitivity analysis and algorithm development (solution technique development).

However, Dykstra (1984) points out some shortcomings that need to be considered in using MP modeling. The model may be formulated so abstractly as to be far from reality. This might make the computation easier but the results meaningless. Conversely, it may not be too abstract but unnecessary details, which have no real effect on the decisions, are added in the model. This clutters the model and results in computational burden. Furthermore, the model might be

2 The algorithmic process begins with an initial trial solution and then the method finds a new and improved solution which is used in the next operation of iteration to solve for an optimum solution. The process is terminated as soon as the optimum solution has been found (see also *stopping rule* in Dykstra, 1984).

developed crudely because of a data-poor system, little understanding and inadequate quantification. If this is the case, the additional information required should be mentioned as the conditions of such experimental model. The model conditions should be considered by users when the results are applied in decision-making process.

In this section, methodological aspects of three selected MP methods are reviewed. LP as a single-objective optimization method is introduced here in order to link the methodological background to the other methods, namely, GP and MOP. They are depicted later as the extension of LP. They are more flexible than LP in the sense that they incorporate more than one criteria within a model. For example, the conventional economic-efficiency objective[3] and other relevant objectives can be considered at the same time in order to present various preferences in society. In addition, other mathematical models like non-LP, integer LP and even dynamic programming as well as special models used in management science and operations research, e.g. network models, transportation model, game theory model can also be transformed to GP models (Schniederjans, 1995).

2.1. Linear Programming

LP is one of many MP approaches that enable the quantification of total net benefit arising from simultaneous uses of land by providing options. According to Bell and Cruz-Trinidad (1996), LP is useful for three purposes: 1) in developing the LP tableau, the resource system is thus structured and quantified; 2) through the primal and dual solution, benchmarks for the DMs are provided;

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3 Economic efficiency is often set as the objective of MP model that aims to allocate the resource in the economy efficiently. The idea is to evaluate the values of objective function coefficients in terms of net benefit (for example, total benefit from each land use activity minus its total cost) via cost-benefit analysis (CBA). Although the conventional CBA is does not consider the distribution of benefits and costs or intergeneration fairness, incorporating of constraints make CBA valid to be used in this case; the MP model itself can absorb this defect of CBA through its constraints. See also Barbier, et al. (1990) who presented the extended CBA to ensure the weak and strong environmental sustainability through an explicit constraint in Kuhn-Tucker maximization.

and 3) through sensitivity analysis, alternative environmental and economic scenarios are simulated. In addition, Dykstra (1984) mentioned that LP is used as a starting point technique which helps to evaluate data needs and provides insight into the interactions among the variables that influence the problem which may be useful to develop more realistic model. Hence, it is not surprising that LP is used worldwide in numerous fields.

LP model consists of a single-linear objective function subject to linear constraints. The model can be a maximizing problem (primal problem) or minimizing problem (dual problem). The objective function of LP model is assumed as a sole criterion for choosing among the feasible values of the decision variables. The analytical unit depends on the problem to be solved i.e. there is no limitation on the kind of units to measure LP objective function as long as they are quantitative and consistent.

The model is bound by the availability of resources, technology or the limitation of external environment. These restrictions are so-called *technological constraints* (resource constraints or physical constraints). Each one consists of the constant-number coefficients of left-hand-side called technological coefficients, each of which represents the contribution to a particular constraint of a unit increase in the activity level associated with each decision variable. The total amount of the resource limitation on the right-hand-side of each constraint is simply called RHS parameter, which is homogeneous. Similar to the logic that applies to the units of objective function, the units of constraints can be any type as long as they are consistent in each independent constraint.

The model constraints develop a feasible region which is independent from the objective function. All LP constraints need to be satisfied (as "rigid constraints") while the objective function is indispensable when it comes to finding the optimum solution.

In addition, each of LP constraints requires equality "=" or inequality "≤ or ≥" type. While other types of equalities "<, > or ≠" do not include themselves on the boundaries of the constraints. In fact, the optimum solution from LP is normally found at the corner point (extreme point) on the boundary of the feasible region (Dykstra, 1984).

The general mathematical structure of LP model is in below.

$$\text{Optimize } Z = \sum_{j=1}^{n} c_j x_j$$

$$\text{subject to } \sum_{j=1}^{n} a_{ij} x_j \{\leq, =, \geq\} b_i \qquad i = 1,2,\ldots,m;\ j = 1,2,\ldots,n$$

$$\text{and} \qquad x_j \geq 0$$

where

x_j = decision variable
c_j = objective function coefficient corresponding to x_j
a_{ij} = technological coefficient corresponding to x_j in constraint i
$_i$ = RHS parameter for constraint i
n = number of decision variables
m = number of constraints

With the LP model, problems in general can be simply formulated by these following steps: 1) define the activity set and the decision variables; 2) specify the objective function as a function of decision variables; 3) specify the technological constraints as well as the identification of the constraint types (equality or inequalities); 4) quantify all coefficients and parameters and ensure consistency of units; and 5) formulate the entire model by setting all steps together.

To solve the model, *geometric method*[4] can be used to deal with a simple model with 2 decision variables, while *simplex method*[5] is widely used not only in LP but also other MP methods. In addition, *sensitivity analysis* is used to test the variation of change in a coefficient or parameter in consideration to the optimum solution. The parameter may be changed in some range without changing the optimum solution through *ranging analysis* (Dykstra, 1984).

Generally, LP optimum solution gives primal values which consist of the optimum value of the objective function (e.g. net profit) and the optimum values of the decision variables. If the relevant resource constraints are included in the model, the solutions will also provide the dual values which represent the opportunity costs of intermediate goods and services such as land, labor, capital and natural resources. In the case of final products, dual values represent the consumer's willingness to pay (Bell and Cruz-Trinidad, 1996).

Although LP approach has been found to be practical and applicable in problem solving due to computational advantage,[6] the results of LP are only as good as the inputs to the model. It is often that large data is needed for analysis. Meanwhile, its assumptions sometimes make the model less realistic. The following are the general underlying assumptions of LP.

1. *Linearity and Proportionality*: The objective function and constraints must be strictly linear, that is, they are required to be first-degree polynomials with the coefficient of the x_0 term equal to zero and all other variables must have exponents of 1. In consequence, each unit of x_j con-

4 G*eometric method* consists of three main steps: 1) find the feasible region; 2) determine the basic solutions (i.e. all possible solutions at corners), and then the basic feasible solution (i.e. a basic solution of LP in which all coordinates are nonnegative and all constraints are satisfied); and 3) choose the optimal basic solution (i.e. a basic feasible solution that optimizes the objective function).

5 *Simplex algorithm* searches for the better basic feasible solution that can improve the feasible result called the *change-of-basis*. The algorithm terminates when no other improved solution exists, that is, the optimum solution is found.

6 An optimum solution is commonly found at one of the extreme points which is called non-inferior solution. Thus, a large LP model can easily be solved.

tributes c_j units to objective function and a_{ij} units to constraints, proportionally. In other words, there is no economy of scale. Furthermore, the linearity does not allow joint interactions between variables. The interpretation of this assumption is that the marginal value of each variable in objective function and the marginal value of resource use in each constraint are constant. For example, land shadow price is constant for any points in the feasible region, and equal to zero for any points in infeasible region.

2. *Additivity*: As a consequence of the linearity, this assumption rules out the possibility of interaction or multiplicative in objective function and constraints. It rather implies that the total value of the objective function equals the sum of the contributions of each variable to the objective function. Similarly, total resource use in each constraint is the sum of the resource use of each variable.

3. *Divisibility*: All decision variables can be any real numbers both integer and fraction.

4. *Non-negativity*: The feasible region is bounded not only by the constraints but also the decision variable axes which are in the positive quadrant. The negative values of decision variables are infeasible. The nonnegative constraints are thus indispensable.

5. *Deterministic*: All coefficients and RHS elements are assumed to be known and fixed. Thus, LP model is sometimes called *non-stochastic* model. In reality, these exogenous parameters are usually uncertain. To deal with the uncertainty problem, sensitivity analysis is conducted in order to observe the variation of the optimum solution when one of the parameters is changed.[7]

7 Grey LP algorithm can deal with the uncertainties of all system parameters as well as with the problem of zero-c_j's. Using the method, sets of grey solutions as possible ranges can be obtained faster than the traditional sensitivity analysis. See Yeh and Tung (2003) and Huang and Moore (1993) for the applications.

Nevertheless, some of these assumptions and disadvantages can be relaxed. For instance, integer linear programming (ILP) will be applied if decision variables are integral numbers or mixed-ILP is applied when one or more of the decision variables are integers. Nonlinear programming (NLP) can relax the linearity assumption of LP. However, Zelene (1974) mentions that LP is sufficiently complex to merit concentrated attention in comparison with NLP which is more difficult to solve. Meanwhile Kantangkul (2000) uses LP rather than NLP in coastal resource optimization due to the complexity of economic activities and the computational difficulty of NLP with proportionally increases with the size of the model. The computational burden of NLP model is also acknowledged by Tarp and Helles (1997).

In addition, incorporating LP with other methods, e.g. simulated annealing (Tarp and Helles, 1997) or modifying of LP, e.g. grey LP (Yeh and Tung, 2003) enhances the capability of the LP-based models. In fact, the LP concept is extended to perform the models with multiple criteria, as depicted further.

2.2. Goal Programming

GP extended itself by reengineering many of the prior single-objective LP models with multiple and/or conflicting (traded-off) objectives. Most of methodologies used in LP problem solving, i.e. simplex method, duality, sensitivity analysis can be equivalently converted to solve GP problem with minor revisions to the algorithms. One main characteristic that makes GP model different from LP and other MPs is that there is no decision variable in the objective function but replaces deviation variables instead, i.e. GP minimizes deviations from multiple goals subject to constraints. The constraints are goal statements and others, i.e. technological constraints and non-negativity constraints (for linear GP). Although the mathematical structure of goal statements looks exactly the same as LP constraints, they do not perform equivalently to LP constraints. LP constraints are rigid, called *rigid constraints* or hard constraints; they need to be satisfied and no violation is allowed while goals perform as *soft constraints* which accept a certain amount of violation of constraints from their targets. In other words, goals are satisfied as closely as possible. Thus goal targets may or may not be achieved.

GP model can be formulated by ranking and/or weighting of goals. Priority factors can be assigned to rank goals and even to make a pre-emptive ordering of preferences. The pre-emptive priority will allow the deviations of the first ranking goal(s) to be minimized and the next priority goal(s) will be allowed, and so on. This variant is known as *lexicographic GP* (LGP). It should be noted that goals can take place with a given priority but cannot be traded-off across the boundaries of different priorities.[8]

In the case that one goal is more important than another in the same priority level then more preference or weight is applied to its deviation variable. Any positive-real numbers can be assigned as relative weights. The model is so-called cardinal-weight model or widely known as *weighted GP* (WGP).

WGP and LGP can be mixed in a model, for example weighted LGP, minimax LGP (see Diaz-Balteiro and Romero, 2003). In the following equations, Model 1 presents as the general form without pre-emptive priority nor weighting. Model 2 is weighted but not ranked while Model 3 is ranked without weighting. Model 4 is weighted and ranked (Schniederjans, 1995). Note that GP model treats a set of rigid constraints (as found in LP model) as an optional set (not shown below). Furthermore, each goal can be a *one-way* or *two-way* type which results in the unwanted deviational variables being minimized in the objective function.[9]

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8 In LGP, the trade-off among goals is possible only when they are in the same priority. This possibility is not allowed across different priorities as they are assumed to be independent of each other in a pre-emptive way. In fact, this situation is not different from the conventional LP structure where no trading-off is assumed to exist between the objective function and the constraint set. LP model performs like LGP in the sense that the LP constraints act equivalently as goals in LGP (except one, i.e. the objective function), which are set as the first priority and must be satisfied to produce a feasible solution. The LP objective function as the remaining goal is included later as the second priority (Romero and Rehman, 2003).

9 Each goal can be either one-way goal ($\leq$ or $\geq$) or two-way goal (equality goal with $\cong$ sign). A one-way goal accepts only underachievement or overachievement but not both at the same

Minimize Z = $\sum_{i \in m} (d_i^+ + d_i^-)$

subject to $\sum_{j=1}^{n} a_{ij} x_j - d_i^+ + d_i^- = b_i$ for i = 1,2,…,m; j = 1,2,…,n

$d_i^+, d_i^-, x_j \geq 0$

and $d_i^+ d_i^- = 0$ for linear GP model

where $d_i^+ =$ positive deviation variable from overachievement goal *I* and $d_i^- =$ negative deviation variable from underachievement goal *i* (1)

Minimize Z = $\sum_{i \in m} (w_i^+ d_i^+ + w_i^- d_i^-)$

subject to $\sum_{j=1}^{n} a_{ij} x_j - d_i^+ + d_i^- = b_i$ for i = 1,2,…,m; j = 1,2,…,n

$d_i^+, d_i^-, x_j \geq 0$

and $d_i^+ d_i^- = 0$ for linear GP model

where w_i^+, w_i^- are nonnegative and can be any real number (2)

Minimize Z = $\sum_{i \in m} P_i (d_i^+ + d_i^-)$

subject to $\sum_{j=1}^{n} a_{ij} x_j - d_i^+ + d_i^- = b_i$ for i = 1,2,…,m; j = 1,2,…,n

$d_i^+, d_i^-, x_j \geq 0$

and $d_i^+ d_i^- = 0$ for linear GP model

where P_i are pre-emptive priority factors (3)

Minimize Z = $\sum_{i \in m} P_i \sum_{k=1}^{n_i} (w_{ik}^+ d_i^+ + w_{ik}^- d_i^-)$

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time. Hence, in GP solution at least one of the deviational variables (either negative or positive deviational variable of each goal) is zero. And both negative and positive deviational variables equal zero when the goal meets its aspiration level exactly. While a two-way goal must be exactly equal to its target, thus both positive and negative deviational variable are unwanted and must be minimized.

subject to $\sum_{j=1}^{n} a_{ij}x_j - d_i^+ + d_i^- = b_i$ for $i = 1,2,\ldots,m; j = 1,2,\ldots,n$

$d_i^+, d_i^-, x_j \geq 0$

and $d_i^+ d_i^- = 0$ for linear GP model

where w_i^+, w_i^- are nonnegative and can be any real number (4)

The basic steps in formulating a GP model are summarized as follows: 1) define decision variables; 2) specify goals including goal types (one-way or two-way goal) and their targets; 3) determine the pre-emptive priorities; 4) determine the relative weights; 5) state the minimizing objective functions of deviations; and 6) state other given requirements, e.g. technological constraints, non-negativity (linear GP model). Note that step 3 and 4 can be omitted. Finally make sure that the model can exactly specify the DMs' preferences.

According to Romero and Rehman (2003), both LGP and WGP are best known and widely used as GP variants (see also appendix I). However, the variants lie heavily on the great amount of information, i.e. goal targets, weights as well as pre-emptive ordering of preferences. These requirements can cause possible weakness if the DMs are not confident of the values of these parameters. In many cases the DMs could not specify meaningful information on weights, or the goals are unrelated to each other so that it is not possible to derive objectively measured preference weights. If it is the case, the relative value of the shadow prices of constraints from the unique-weight GP run can be used to derive the real preference weights. The argument is that the initial run with the unique weight *per se* can be biased although this technique makes the weighting more defensive than a subjective weighting (Dykstra, 1984:243).[10]

If it is difficult or impossible to get related information from the DMs, the implementation of sensitivity analysis by various weighting and ranking scenarios or change in goal types provides a large number of solutions without the prior information required from the DMs. Thus sensitivity analysis can provide infi-

10 Referred to this technique which introduced by Ijiri in 1965.

nite solutions as information rather than just a single-point solution as numerical result. In this sense the DMs not only use the information to visualize the various alternatives but also to ascertain whether the model correctly reflects their intentions. The DMs are then asked to reach a consensus on the best compromise solution in which the ranking is often reshuffled.

The GP solution has a high tendency to be inferior[11] (dominated) with respect to technological constraints. To deal with this drawback, Field et al. (1980) present a technique to ensure non-inferior GP solutions. The technique is to use GP and LP as a complementary package. Tamiz et al. (1998) suggests straight restoration, preference based restoration and interactive restoration which employ cardinal weightings in LGP to ensure non-inferior solutions. Rehman and Romero (1993: 246) conclude that the generation of inferior solution is no longer a serious problem associated with GP due to the availability of the refinement techniques.

In fact, inferior solution is not always a problem as long as the model is correct. It is a problem only if the model does not reflect the DMs' actual preferences. In some cases, non-inferior solution may not be intrinsically superior to inferior solution especially in the case of natural resource problems, as described by Dykstra (1984: 235-238).

Other controversial issues surrounding GP, are incommensurability,[12] naïve relative weighting or prioritization,[13] redundancy goals, incompatibility of LGP

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11 The solution does not lie on the boundary of feasible region, that is, achieved value of the objective can be improved without worsening the level of another objective. It means other superior solutions that yield better solutions exist. In contrast, non-inferior solution (or nondominated solution) presents the best solution or Pareto efficient solution. Note that a GP solution will be non-inferior only if the ideal solution (with zero deviations from all goals) is either infeasible or lies on the boundary of feasible region defined by the technological constraints (Dykstra, 1984: 238).

12 Incommensurability is occurred when goals apply different units, so that deviational variables are measured in different units and they are summed up directly—just like mixing up orange and apple. It causes a distortion in favor of high numerical-valued goals.

13 The problems with wrong proportional weighting or prioritizing.

achievement function with the utility function[14] etc. It should be noted that a single flaw can ruin the entire model and cause poor modeling or modeling error[15] (Rehman and Romero, 1993; Schniederjans, 1995).

Some techniques and variants developed to avoid the pitfalls and enhance the capability of GP are: normalizing techniques,[16] analytic hierarchy process (for determining goal weight and priorities) or conjoint analysis, regression analysis (for determining relative weighting or goal constraint parameter estimation), logarithmic transformations of goals (to convert nonlinear to linear GP), minimax GP (Chebyshev), penalty function, using heuristic approach such as genetic algorithm, simulated annealing, etc.

Nonetheless, one critical disadvantage in using GP remains: the large amount of precise information on target values, weights and pre-emptive priorities required from the DMs. Sensitivity analysis and interactive GP are recommended to deal with this drawback (Rehman and Romero, 1993).

Some points to be concerned on the development of GP models are emphasized by Tamiz et al. (1998), as follows:

1. The right GP variants should be chosen so as to be coherent with the DMs' preferences

2. Normalization and Pareto efficiency detection and restoration can be used to avoid the modeling pitfalls

3. The reliance on the single GP variant is not justified. In most real-life cases, several variants should be conducted.

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14 LGP does not serve theoretical interest in the sense that it does not lead to the maximization of the utility function of the DMs.

15 As Tamiz et al (1998: 571) mention the case that an inefficient objective and an unbound objective cause the entire model inefficient and unbound.

16 It is used to deal with incommensurability. There are several techniques such as percentage, Euclidean, summation and zero-one normalization as depicted in Tamiz et al. (1998).

4. LGP models are valid for the decision models with discontinuous preferences. If used, LGP models should not include an excessive number of priority levels because of problems with redundancy.

In sum, the development of GP techniques so far allows it to be used validly in modeling of relevant natural resource problems. It is also deemed as a practical approach in dealing with a large model with many goals, unlike MOP which is discussed next.

2.3. Multi-Objective Programming

It is sometimes presumed that MOP and GP are the same methods. Though both are used to solve multiple criteria problems in which conflicting objectives are commonly involved, the models are in fact formulated in different ways. When there is insufficient knowledge to define goal targets, MOP is useful. All details on goal achievement levels, preference weights and priorities must be known in advance when GP is applied but this are not required in MOP. In technical terms, the main idea of MOP is to distinguish non-inferior solutions from inferior solutions. In this sense, MOP does not represent the DMs' preferences as GP does but rather establishes a set of efficient solutions[17] which the DMs can use as a basis to arrive at a consensus on the best solution. That is, MOP seeks to identify the set of efficient solutions, $\underline{Eff}\ \underline{Z}\ (x)$, from multiple objectives, $Z_1(\underline{x}), Z_2(\underline{x}), \ldots, Z_q(\underline{x})$, as shown below.

$$\underline{Eff}\ \underline{Z}\ (\underline{x}) = [Z_1(\underline{x}), Z_2(\underline{x}), \ldots, Z_q(\underline{x})]$$
$$\text{subject to } \underline{x} \in \underline{F}$$

where $\underline{F}$ is the efficient set of feasible solutions.

Generally speaking, the structure of MOP model is almost the same as that of LP. The main difference is that MOP comprises more than one objective subjects to constraints and non-negativity property. It is presented as follows.

17 Pareto optimal solutions along the production possibility frontier.

Optimize $Z_1(\underline{x}) = \sum_{j=1}^{n} c_j x_j$

Optimize $Z_2(\underline{x}) = \sum_{j=1}^{n} c_j x_j$

.

.

.

Optimize $Z_q(\underline{x}) = \sum_{j=1}^{n} c_j x_j$

subject to constraints:

$\sum_{j=1}^{n} a_{ij} x_j \{\leq, =, \geq\} b_i$ $\qquad i = 1,2,\ldots,m; j = 1,2,\ldots,n$

and $x_j \geq 0$

where

x_j = decision variable
c_j = objective function coefficient corresponding to x_j
a_{ij} = technological coefficient corresponding to x_j in constraint i
b_i = RHS constant for constraint i
n = number of decision variables
m = number of constraints

In sum, the efficient set of solutions from MOP is at change-of-basis points on trade-off possibilities frontier. It means that it provides the efficient set of Pareto optimum solutions which are non-inferior. The trade-off values between conflicting objectives represent the opportunity costs in economic sense. This way, the consequences associated with various efficient choices are known in advance.

There are three basic methods to solve MOP problems other than graphical method. These are the constraint method, the weighting method, and the multi-objective simplex method (Romero and Rehman, 2003).

The *constraint method* traces out the region over which there are tradeoffs among the objectives by making systematic changes to the RHS parameters of one or more constraints.[18] The technique is sometimes called *parametric RHS* or systematic sensitivity analysis (see also Dykstra, 1984: 249-254). The initial information over the efficient set of feasible solutions can be obtained by using a square matrix or a pay-off matrix.[19] The matrix provides the interval of each RHS-parameter between ideal and anti-ideal point that contains the feasible set. The interval is thus used as the upper and lower boundary for the range over which the L_w can vary when one of the objectives, $Z_v(\underline{x})$, is optimized while the others, $Z_w(\underline{x})$, are specified as constraints.

Optimize	$Z_v(\underline{x})$
subject to	$\underline{x} \in \underline{F}$
and	$Z_w(\underline{x}) \leq L_w$

Secondly, the *weighting method* combines all the objectives into a single objective function. Each objective is given a weight. The efficient set is generated through parametric variation of weights. In other words, these weights are treated as parameters (while the constraint method uses RHS values) that can be varied systematically to generate the efficient set. Thus, the set of weighted combination is infinite which implies an infinite set of marginal rate of transformation along the trade-off function. The weights, in this sense, are not interpreted as the DMs' preferences. The mathematical structure is:

Maximize	$w_1Z_1(\underline{x}) + w_2Z_2(\underline{x}) + \ldots + w_wZ_w(\underline{x})$
subject to	$\underline{x} \in \underline{F}$
and	$\underline{w} \geq 0$

18 The constraints mentioned here are in the same sense as soft constraints in GP but RHS values are not required in advance.

19 The pay-off matrix consists of the ideal and anti-ideal points (nadir points) obtained by optimizing each of the objectives separately as modelled in LP over the efficient set. The optimum solution of the objective function in consideration is its ideal point and its associated value of the other objective called anti-ideal point.

Lastly, the operation of *multi-objective simplex method* is to find all the extreme points by moving from one extreme point to another. This method guarantees the exploration of all extreme efficient points while the above two methods may not. However, its computation is practical only for small problems.[20]

It should be noted that the constraint method guarantees efficient solutions (both at extreme and interior points) only when the parametric constraints are binding[21] in the optimum solutions, otherwise the solutions may be inferior. Meanwhile the weighting method guarantees the efficient solution only when $\underline{w}>0$ and the method gives the efficient set merely on the extreme points not on interior points (Romero and Rehmen, 2003).

It can be concluded that most of the weaknesses of MOP methods are operational and computational in nature while the advantage of the methods are to seek for Pareto optimum solutions which may not be fulfilled by GP methods. The computational burden is large[22] especially when they are used to solve realistic natural resource problems with more than 3 objectives (Dykstra, 1984; Romero and Rehman, 2003).

Notice that MOP methods do not involve the decision-making process but rather provide a set of efficient solutions. It can be the case that a particular MOP model gives undesirable solutions with a large set of efficient solutions which makes decision-making difficult. The compromising programming (CP)

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20 The multi-criteria simplex based software "ADBASE" is available which make the solving of large models possible. However, it has the capacity to solve the problem with the maximum of 50x50 matrix and no more than 3 objectives. The computational effort of other techniques is also discussed in Rehman and Romero (1993).

21 A binding constraint does not only bound the feasible region but also indicate the optimum solution. While nonbinding is in opposite.

22 As Rehman and Romero (1993) point out that it needs R^{q-1} LP runs or P^{q-1} LP runs for the constraint method and the weighting method respectively to obtain the efficient set—where R is the number of subintervals over which the range of objectives treated as restraints; P is the number of values given to the weights; and q is the number of objectives.

technique is then useful in the next step to help the DMs find the best solution or the compromise set of solutions.[23]

3. Review of Applications to Natural Resources and CLU

This section reviews the selected cases of MP application. It aims to explore how both single-criterion and multi-criteria approaches are being applied so far in areas of natural resources especially in coastal resource and land use problems.

3.1. Single-Criterion Approach: LP

The application in the fishery and forestry sector done by Araneda, E. et al. (1996) in the case of Bío-Bío, Chili is to find the optimum solution of the amount of fish handled at each stage of production (from capture to sales) and the quantity of wood products. Tourism sector is not considered because of insignificant contribution to revenues, although the study mentions the benefits from the sector in terms of income and employment generation.

The model objective function is to maximize net benefit from those two sectors. The objective consists of both revenue and cost attributes for the decision variables. On the revenue side are the economic sectors (fishery or forestry), types of markets (domestic or international market) and final products (fresh/ frozen/ dried/ canned fishes, fishmeal, logs, pulp, chips, plywood, veneer and firewood). On the cost side are the sectors, scale of operation (small or large scale), technology (capital or labor intensive), gear or method used, resource used/ fi-

23 CP is one of MCDM techniques which is sometimes called ideal point technique. CP is a proxy measure of the DMs' preferences which assumes that the most desirable solution is the ideal one. One of the CP techniques, the *discrete approximation*, searches for one of the efficient solutions that gives the closest distance to the ideal point. While the *continuous setting* method gives compromise set of solutions by reducing the efficient set in desirable size. See more on technical aspects in Romero and Rehman (2003) and Romero (1996). For the sample of application, see Pereira and Duckstein (1993).

nal products, and activities or stage of production to reach final products. The external cost of water contamination from fishmeal plants is also internalized in the objective function as cost of freshwater pumping in order to dilute the effluents to be maintained at an acceptable standard of dissolved oxygen. The model does not include biological limits (i.e. biomass for fishery, maximum allowable cut for forestry and technological limits in fishmeal plant processing capacity) as real resource constraints but rather employs the balance and the convexity constraints. Only land availability for forest plantation is set as a resource constraint.

The final LP tableau consists of a 782x530 matrix. The optimum solution shows that forestry sector contributes 87% of optimum total net benefit. However, the water contamination by fishmeal plants diminishes the total net benefit by 20 USD per year. The dual values are not analyzed due to the absence of real resource constraints.

Another relevant literature is on the alternative land uses of mangroves in Guayas, Ecuador done by Bell and Cruz-Trinidad (1996). The case is pointed out as a question of the conversion vis-à-vis conservation of mangroves which involves foregoing present short-term gains from shrimp aquaculture for long-term benefits. (Shrimp culture has been the main cause of mangrove conversion in Ecuador because of attractive return in the export market).

The LP objective function is to maximize net social benefit (NSB) based on total economic value (TEV) approach.[24] NSB in this case is derived from the op-

24 As concluded by Cruz-Trinidad et al. (1996) TEV plays great role on LP solution. Theoretically, it is required to consider NSB based on TEV and impact analysis when maximizing NSB is set as the land use objective function. TEV approach would account for the values of environmental resources both market and non-market goods and services while the implementation of impact analysis aims to measure external costs and external benefits. The framework as such performs land use options within the DMs' awareness of the whole effects. The analysis also shows that the optimum land use allocation using TEV approach gives a greater total net benefit result than using direct cost and revenue approach. Mangrove areas would be conserved in TEV approach result, but all of them are converted to milkfish culture in direct cost and revenue approach result. Bell and Cruz-Trinidad (1996) as well as Araneda et al. (1996) also apply

timal combination of land uses between conversion of mangrove to shrimp farms and sustainable exploitation of mangroves. The decision variables of mangrove conversion are land area, area converted to shrimp farms (extensive or semi-intensive system), quantities of shrimp harvested and sold. While the decision variables of sustainable exploitation are land area, forest area exploited, quantities of trees felled, fishing effort (categorized by mangrove zones and species) and quantities of fishery and forestry products sold.

The constraint set consists of resource constraints, i.e. land areas in different zones of mangrove, maximum carrying capacity of forest and fishery, availability of production inputs (shrimp seed, labor and capital), and maximum capacity of effort, processing plant and cold storage. The balance equations (the simulated resource flow to final product), convex equations, counters and non-negativity constraints are also included.

The primal solutions show decision variable values as well as TEV at optimum level. Sustainable exploitation strategy contributes 60% of TEV. The remaining is accounted by conversion to shrimp farms. The dual values are analyzed. The conversion of salt-flat to shrimp farms provides higher marginal value than the conversion of mangrove to shrimp farms. Shrimp fry emphasizes the role of mangrove in coastal livelihood by giving the highest shadow price amongst others (the shadow prices of other forestry and fishery products). While the dual values of shrimp post-larvae from hatcheries and labor inputs are zero, i.e. they are non-scarce.

The up-to-date relevant study is found in Kantangkul (2000). This study applies LP to formulate the model of coastal resource utilization problem in Trang province, Southern Thailand.[25] The competing activities in consideration are

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TEV approach to their LP models through the objective function coefficients. Bell and Cruz-Trinidad (1996) formulate the model to maximize TEV derived from the mangrove ecosystem. While Araneda et al. (1996) internalize the effects of fishmeal plants when optimize the net economic value from fishery and forestry.

25 This case is raised on the problems of the unsustainable use of coastal resources and the rapid expansion of intensive shrimp farms. The destruction of mangrove from (legal and illegal) log-

rubber plantation, rice field, mangrove conservation, plantation and logging including the conversions of existing rubber plantation, rice field as well as mangrove zone B to shrimp farms. Shrimp farming is classified into low and high stocking practices. Land use options in each year for these activities are defined as decision variables. The model timeframe is set for a 30-year periods from 1990 (when shrimp farming began in the study area) to 2019. The land uses from 1990 to 1994 are restricted as the existing activities. The model is so-called *multi-period LP*. The objective function is to maximize total present value of net benefits from all activities subject to constraints. The model constraints are the availability of land, labor and capital for each land use activity, ecological constraints, and resource transferring constraints of related years (balance constraints).

The positive and negative impacts on the environment are incorporated in the model in several ways. The benefits from mangrove in terms of nutrients release (from mangrove litter-fall), supporting livelihood[26] and commercial fisheries[27] are internalized through the objective function coefficients. The ecological constraints in terms of the environmental capacity of the nutrient balance (nitrogen and phosphorous discharged from shrimp farming and trapped by mangrove) are considered. The input-output coefficients of the nutrient loading and trapping per area unit are identified for each of the constraints. Lastly, the maximum capacity of mangrove for logging is used as RHS-parameter in each mangrove yield constraint.

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ging and conversion to shrimp farms degrades fisheries stock and productivity. Without prior treatment of effluent brackish-water and sludge from shrimp farms causes spill-over effects to other resource users, for example, rice farmers and coastal people livelihoods that generally depend on mangrove products and functions.

26 Livelihood supportive values consist of the values from artisanal fishery and traditional uses of mangrove, e.g. firewood, medicines, construction materials and nipa palm) by coastal dwellers.

27 Regression analysis is applied to estimate marginal fishery yield (catch rate) of mangrove-dependent species over the period. The value of mangrove in term of supporting fisheries is then calculated by multiplying marginal yield with the average price. Regression analysis is also applied to predict shrimp yields from 1995-2008 and the coefficients are used to calculate

The main result shows the optimum land use in each year for each activity. The interpretation from the numerical result is that the conversion of existing rubber plantations and rice fields, but not of mangrove area, to shrimp farms is allowed. However, shrimp farming in former mangrove, rice field and rubber plantation areas after year 2002, 2004 and 2006, respectively will not be profitable. That means after those years all ponds will be abandoned.[28] Conserving mangrove is recommended instead of granting wood concession. Labor and capital resources do not restrict the model after 1995 and 2000, respectively.

Unlike Araneda, E. et al. (1996), this study does not internalize external cost (from shrimp farming) in the objective function coefficients but rather internalizes it as ecological constraints (nutrient loading). The argument is that the optimum values (both net benefit and optimum land use) may be significantly different between these two frameworks. However, in some cases the full accounting of externalities is not possible for many reasons. Using valid environmental constraints and sensitivity analysis are technically sound in providing insight.

In addition, the consideration of long timeframe is reasonable when the problem involves the ecological aspects. Nevertheless, the effects of uncertainties may be argued. Sensitivity analysis can be used to correct this shortcoming. Large data sets are required to estimate all parameters.

Another method to deal with uncertainties of the model parameters, Yeh and Tung (2003) employs grey LP algorithm rather than the traditional sensitivity analysis. The methodology provides the information on the possible ranges of optimum solutions in corresponding to grey intervals (the variations of all parameters over their ranges). It is applied to identify the land use management strategy for coastal areas in Taiwan where there is a problem of land subsidence from abstraction of groundwater in multiple land uses, mainly agriculture and fish farming. Decision variables are total land use areas (for agriculture, fish

the private benefits from shrimp farming over the period. These numbers are put in the multi-LP model as the objective function coefficients.

28 The cumulative area is around 4,600 ha which is double of the situation in the 1994.

farming, industries, commerce, recreation, conservation, etc.), land conversion (from existing land use to alternative uses), and water supplies (by surface water, groundwater, alternative sources). Constraints are water demand; surface water and groundwater supplies (at safety yield); land availability, balance constraints of land areas, and lower-upper limits of land use types (defined from policy level); and non-negativity constraints. The LP model is firstly formulated in problem identification process. The objective function in this case is to maximize total net financial benefit (benefits from land uses minus costs from water consumption). The model is then modified to grey LP when optimized. The results obtained in term of ranges of solutions indicate the reallocation of land uses and water supplies, i.e. existing agriculture and fish cultivation areas can be transferred to alternative uses. Groundwater should not be used for fish farming any longer. Nonetheless, traditional sensitivity analyses are required somehow if the range in question is wider than the grey interval.

However, based on the similar resource problem as Yeh and Tung (2003), Sethi et al. (2002) use traditional LP model instead to obtain the optimum cropping and groundwater management strategy for maximizing economic benefits in a coastal river basin in Orissa State, India. The constraints in consideration are water allocation for crops, land availability, water availability, hydrological balance of aquifer, irrigated-crop area limits (to meet the local food requirement) and non-negativity constraints.

Noticeably, unlike the above studies, environmental values are not taken into account in these last two studies, though some environmental constraints are internalized implicitly through constraints.

3.2. Multi-Criteria Approaches: GP and MOP

The optimization model based on a single criterion does not often give acceptable solutions in practice especially in the case of natural resources. Romero and Rehman (1987: 62) deemed that in management of natural resources, the social and environmental aspects of resource allocation cannot be ignored if the decisions taken are to be treated as realistic. In other words, the natural resource problems in real world are multi-dimensional problems which require analysis within a multi-criteria framework.

Multi-criteria methods have been applied extensively to natural resource problems but not specifically to coastal lands. For example, Romero and Rehman (1987) review the applications of GP and MOP in fisheries, agricultural land uses, forestry and water management. The finding appears as table 1. Hayashi (2000) reviews the applications of multi-attribute utility theory as well as GP and MOP in agricultural resource management in which the discussion of the application characteristics and pitfalls is included. Meanwhile, two entire volumes (94 and 95) of Annals of Operations Research (2000) contribute the applications to agriculture, fisheries and forestry. Other literature, obtained from literature surveys and sources of collections, are listed in appendix II.

Reviewing of applications in areas of natural resources is fruitful to some extent by providing the idea for a framework on the applications to CLU. A brief review of selected studies follows.

As noted in section 3.1, internalizing environmental values in the optimization model is crucial. Thampapillai and Sinden (1979) is one example of the attempt in doing so. However, unlike the common cases as shown in a single-objective approach which impacts are internalized as the objective function coefficients or constraints, this study considers them as the traded-off objective. It means that the maintenance of environmental quality objective by protecting the areas from the development is in conflict with the economic-efficiency objective, i.e. maximizing income from land development for agriculture, forestry, mining and housing in this case. The transformation curves are derived in various scenarios corresponding to different environmental functions evaluated mainly on the basis of social willingness to pay. The curves represent the opportunity costs resulting from various weights.

The practical framework that closely relates the CLU problem in question is found in Chang et al. (1995). The study applies MOP techniques to land resource allocation in the Tweng-Wan watershed in Taiwan. The model consists of 6 decision variables (i.e. areas of forest conservation, agriculture, residential, grass land, stock farming and recreation) and 6 objective functions of land development. The objectives are based on maximizing economic benefits in terms of employment and income and minimizing water pollution in terms of total discharges of phosphorus (P) and nitrogen (N), biological oxygen demand (BOD), and sediment. The constraints are land availability, minimum forest area, soil property, minimum agricultural area (self-sufficiency restriction), minimum residential area, land slope, minimum recreation area, the assimilative capacities of P, N and BOD as well as non-negativity constraints. The model is solved by using CP and multi-objective simplex method. The result shows that the residential area could increase if pollution is controlled. The livestock husbandry should not increase.

Other studies have contributed to the technical development of multi-criteria methods applied to natural resources. Bertomeu and Romero (2001) use a zero-one GP to deal with the computational problem of the existence of absolute values in the constraint set and infeasible solutions in the case when the biodiversity characteristic is considered in forest harvest scheduling optimization. The software, IGPSYS, is recommended due to its property of being able to reduce computational burden of the proposed model. Linares and Romero (2002) present a GP methodology that allows the aggregation of individual preferences provided by social groups towards different interests. The methodology is applied to electricity planning in Spain where conflicts over economic and environmental criteria are involved. Diaz-Balteiro and Romero (2003) developed a GP model that incorporates carbon sequestration, in terms of total carbon balance, as a complementary objective with other criteria (i.e. maximizing net present value, equality of harvest volume, area control and ending inventory) in forest management in Spain. Pay-off matrix of the five criteria shows nonviable results from a single-optimization policy. Hence, the best compromise solutions amongst the five criteria using weighted and minmax LGP are suggested.

It is noticeable that the multi-criteria approach is being applied to various natural resource problems. Some studies focus on the development of techniques to make the applications to be used practical and realistical. Others contribute the application frameworks in particular problems and provide the results as information and policy options. Interestingly, most cases show that environmental aspects do not merely occur as constraints but as either conflicting or complementary objective(s) or goal(s). In addition, the methods that are being developed recently also aim to take into account different preferences of people in the society.

Table 1. The examples of goals/ objectives in multi-criteria approach in cases of natural resource problems

Area	Optimization Problem	Decision Variables	Goals/ Objectives	Methods	Literature
Fisheries management	Mainly to optimize the structure of the fishing fleet in a specific area and the fish processing plants	Decision variables range from vessels of different types and sizes	Min. operating losses, deviations from quotas and disruptions from the status quo	Nonlinear MOP	Garraod and Shepherd (1981) Shepherd (1980; 1981)
			Max. of catches, profits, level of employment	MOP	Bjørndal (1981)
				Interactive MOP	Mathiesen (1981)
			30 goals such as yearly catch divided among various species, fish deliveries per month, tax inflow from fishing	LGP	Amble (1981)
			3 goals represent cost of fishing, an aggregated yearly catch for all the species and the maintenance of employment	WGP	Drynan and Sandiford (1985) Sandiford (1986)
	Management of Skeena watershed in US	Number of certain types of salmon harvested in a given year	trade-off goals between salmon harvested and power production	Nonlinear WGP	Everitt (1978)
	Lake management	Number of different types of fish harvested	3 prioritizing goals: economic goal (budget), biological goal (maintain the existing rainbow trout population and sociological goal (improve fishing quality for angler satisfaction	LGP	Weithman and Ebert (1981)

Table 1. (Continued)

Area	Optimization Problem	Decision Variables	Goals/ Objectives	Methods	Literature
Agricultural land use	Planning of an hypothetical 600 acres mixed farm in UK.	Land use activities such as acres of barley to be grown, number of cows to be kept	Gross margin, seasonal cash exposure and provision of stable employment throughout the year	WGP	Wheeler and Russell (1977)
	Planning in Sacramento Valley		3 goals: red meat production, use of fossil fuel energy and profits	LGP	Bartlett and Clawson (1978)
	Farm planning problem in subsistence farming in the Philippines		6 goals-enough rice for family subsistence, sufficient cash surplus, etc. are grouped into 5 priorities	LGP	Flinn et al. (1980)
	Land allocation problem in Australia		2 conflicting objectives: money income and environmental benefits	The weighting method of MOP	Hitchens et al. (1978) Thampapillai and Sinden (1979)
	Land allocation problem in India		The tradeoffs between net economic benefits and total area of irrigated crops	The constraint method of MOP	Vedula and Rogers (1981)
	The implementation of an agrarian reform program in Spain		3 objectives: farm gross margin, level of employment and seasonal labor	CP	Romero et al. (1987)

Table 1. (Continued)

Area	Optimization Problem	Decision Variables	Goals/ Objectives	Methods	Literature
Forestry planning	Optimum land use of forest area	Acres of land use activities in each geographical region	Many conflicting goals: levels of profits, budget limits, timber harvesting targets, providing recreation or hunting facilities for a given number of days per year and conserving wildlife by maintaining a desirable number of some animal species	GP	Field (1973)
	Optimum forest rotation for timber harvest scheduling	Acres harvested in various age-classes of timber for a each time period	Total volume of timber harvest, net present value, harvesting the same amount of timber during each period and age-class of trees occupies the same area in each period of time	LGP	Kao and Brodie (1979) Field et al. (1980) Hotvedt et al (1982) Hotvedt (1983)
				MOP	Ritters et al (1982)
	Reforestation problem			Interactive LGP	Walker (1985)

Table 1. (Continued)

Area	Optimization Problem	Decision Variables	Goals/ Objectives	Methods	Literature
Water resources	River basin planning involves determining the number, location and size of different projects to be established along the basin of the river in order to meet the constraints of the situation and to optimize various objectives		Max. economic efficiency (national incomes) and regional equity (absolute deviations from an equal regional water distribution)	The constraint method of MOP	Major and Lenton (1978)
			Max national incomes, quality of the environment and equitable regional allocation of water	MOP; TRADE; integer LGP; interactive SWT	Byers (1973); Goicochea et al. (1979); Das and Hamies (1979)
	Efficient operation of reservoir system		Optimizing water supply for industrial, municipal and agricultural uses, max. hydroelectric energy production, min. the risk of flood and keeping a stable water level for recreational navigation	MOP	Croley (1974) Cohon et al. (1981)
				LGP	Chisman and Rippy (1977)
				MODP	Tauxe et al. (1979)
	Water quality planning		Optimizing the cost of waste removal, min. inequalities and maintaining water quality standards	Interactive MOP; MOP; interactive nonlinear GP; LGP; nonlinear MOP	Manarchi et al. (1973); Brill et al. (1976); Manarchi et al. (1975);Lohani and Adulban (1979); Arikol and Basak (1985)

Source: Modified from Romero and Rehman (1987: 65-71).

4. MP in Geographical Information System Environment

Geographical information system (GIS) is being used predominantly in the area of multi-criteria decision making (MCDM).[29] It is used as a decision support system in resource allocation (e.g. land evaluation and allocation) and policy decision problems. Using GIS today is thus not only to inform but also to serve as a modeling tool which benefits the decision making process by simulating the spatial effects of predicted decision behaviors. It can collect, assess and produce data of a type that suits optimization. It can also be used to assign priority weights to the criteria, to evaluate the feasible alternatives and then to visualize the result. All these actions can be done within one system. A GIS software "IDRISI", for instance, has the capability to deal with land use allocation problem with multi-criteria and multi-objectives and present the final allocation results into a map.[30] This task cannot be accomplished by using MP alone.

The following review is based on some selected studies done by Aerts, et al (2003a); Aerts, et al (2003b); Aerts and Heuvelink (2002); and Grabaum and Meyer (1998). It aims to present the potential of GIS combined with optimization techniques in solving land use problems in general cases to which the term "multi site land use allocation" (MLUA) problems is referred.

29 MCDM-GIS has been used since early 1990s and became very popular in late 1990s. At present (2003), a large number of studies are coming up with new frameworks and applications in various cases as well as for software development. Two basic techniques of MCDM used in GIS environment are multi-criteria evaluation (MCE) and optimization techniques. MCE is an evaluation technique used when the alternatives can be defined in advance and are interactively evaluated against each other (see Sharifi et al., 2002 for an example of MCE-GIS application). However, when the alternatives are not available or difficult to define, the optimization techniques are used to provide the optimal allocation alternatives. The later techniques are called spatial design techniques in some literature (Aerts, et al, 2003a; Aerts, et al, 2003b).

30 See also the user's guide by Eastman (1997). The manual provides a case study of an expansion of the carpet industry in an agricultural area in Nepal. GP model in MOLA module (optimiza-

Grabaum and Meyer (1998) generate land use options to serve multi-functional uses of the 48 km^2 landscape in Saxony, Germany. The multi-criteria optimization combined with GIS is applied. The regulated functions, i.e. soil erosion hazards by water, water discharge regulation, groundwater regeneration including agricultural production capability (soil values) are set as optimizing goals. Some goals conflict with others, for example, increasing agricultural production versus prevention of soil erosion. Each goal function is assessed[31] in linkage with GIS to arrive at the functional assessment values (in ordinal scale) which are then used as input data (coefficients) in multi-criteria optimization. The values provide the information to the optimizing process (i.e. the areas are allocated based on their different functional values). For example, the areas with high assessment values of soil erosion must be converted into forest and grassland instead of agriculture, the sites with high soil values must be maintained for agricultural crop sites, and so on.

Decision variables are defined by alternative land use types, i.e. agricultural land, grassland and forest. They are considered on the basis of a particular polygon of existing land use which is either in arable land or pits. That is 82% of the total area are considered in the analysis while the settlements, conservation areas, forests, grassland are not. The number of decision variables is equal to the number of alternative land uses (i.e. three types) multiplied by the number of polygons within arable and pit areas (1,729 and 146 polygons respectively).

Each goal function is optimized independently from other functions by using LP in order to calculate optimum values for each function in which compromising solutions can be found. Equality constraints are the areas of polygons. And inequality constraints are the lower and upper area boundaries for each land use type that can be assigned. The deviations of the goal functions are minimized and weighted by various scenarios obtained from the DMs. An arbitrary set of

tion process) combined with MCE module (evaluation process) within IDRISI for windows are used to find the optimum solution and to develop the zoning map.

31 For example, Universal Soil Loss Equation (USLE) is used to assess soil erosion hazards.

solutions can even be calculated interactively by subjective weighting of goal functions.

The technical linkage between optimization process and GIS is examined. The UNIX-based GIS software Arc/Info is used to assess selected regulation functions (soil erosion hazards by water, water discharge regulation, groundwater regeneration including agricultural production capability). The values from the assessment in polygon attribute table (PAT) form are exported from Arc/Info and used as the input data (coefficients) in the optimization program—LNOPT, PC-DOS based. After the optimization is carried out, the solutions for all polygons are stored in the optimization database, which are then put in PAT again and reimported into GIS in order to evaluate optimum land use maps. It is to be noted that the optimization process in this case is not operated inside GIS; rather, the optimization process and GIS are integrated and support each other via data-export files in file exchange module. This framework is called *loose coupling strategy* as mentioned by Gomes and Lins (2002).[32]

The analysis provides the results of the land use options from different scenarios, i.e. maximized soil erosion protection scenario shows that the agricultural land should be decreased 15% while the grassland and the forest areas should be increased 205% and 333% respectively compared to actual land use. This scenario gives the maximum loss of agricultural land. Meanwhile, the result shows minimum change of arable land when either agricultural production goal or groundwater regeneration goal is maximized. The multi-criteria optimization

32 MCDM can be integrated with GIS exogenously called loose coupling strategy or endogenously called tight coupling strategy. The specific GIS software, IDRISI (http://www.clarklabs.org/) and SPRING (Georeferenced Information Processing System-http://www.dpi.inpe.br/), are the examples of the tight coupling strategy implementation. Gomes and Lins (2002) implement the loose coupling strategy to select the best alternative district in Rio de Janeiro that represents the closest characteristics of quality of urban life given by the DMs. MCDM-GIS in this case helps to reduce the set of alternatives which, thus, reduces the computational burden in the optimization process. Interactive MOP model, Pareto race method, is applied in the optimization by using VIG software (a visual interactive approach to goal programming). The disadvantages of other software, ADBASE and TRIMAP, in solving this model are also discussed.

with the higher weighting factors for both soil erosion protection and agricultural production goals shows the compromise solution.

The practical problem regarding this application is that it requires a large quantitative basic data. This study also points out some issues for further study such as the application of the method for complex land use planning processes, the integration of socioeconomic assessment data in the optimization problems, and the possibility of linking the method with dynamic models, for example, dynamic soil model or dynamic optimization model.

Aerts, et al. (2003a) explore whether linear optimization methods are suitable for practical use in a decision environment in terms of the solution time for MLUA problems and how a spatial compactness objective can be incorporated into the optimization model.

The MLUA model is set to minimize the land use development (land use change) costs among different types of land use in the study area. The area is divided into a grid. Only one type of land use can be assigned in each cell, thus each decision variable is equal to 1 if that cell is assigned for a particular type of land use and 0 otherwise. In this way, the model is defined as integer programming. The different proportions of numbers of cells are used as constraints in order to bound total numbers of areas assigned for various land use types.

Spatial objective is integrated with the MLUA model as maximized compactness objective of the allocated land use. To solve the model when the compactness objective is included, either “heuristic approach” or “exact approach” can be used. Heuristic approach, for example, simulated annealing used by Aerts, et al. (2003b) and Aerts and Heuvelink (2002), is capable of solving large combinatorial optimization problems but does not guarantee the optimum solution. While exact linear integer programming (LIP) solved with LP solvers can be slower than heuristic algorithm but it guarantee an optimum solution.

In addition, Aerts, et al. (2003a) refer to Cova (1999) that LIP models including compactness objective can easily be solved if they are small-sized problems, up to 8x8 cells, with commercial LP solvers like CPLEX or LINDO. However, Aerts, et al. (2003a) develop higher capacity models that can solve larger problems which are more than 10x10 cells, and with fast computation.

The performances of three linear integer programming (LIP) and one nonlinear integer programming (NLIP) models developed for MLUA problem solving are explored. The basic concept is to optimize trade-off goals, i.e. minimized land development costs and maximized compactness of neighboring cells that have the same land use types. Both goals can be weighted in various scenarios. Model 1 performs the nonlinear compactness objective function, while one of three LIP models, model 2, is acquired by transforming the nonlinear compactness objective function into LIP model. The compactness objectives of the other LIP models are formulated in different ways. One of them, model 3, is to include parcels of land within protected reserve. Each reserve consists of core areas surrounded by buffer areas. Thus the compactness objective is obtained by minimizing the number of buffer cells around each cluster core areas. The decision variables for both core cells and buffer cells are defined as the binary variables as discussed above. The last, model 4, aggregates individual cells into blocks and then minimizes the number of blocks that contain the same land use type in the final result.

"What's Best!" the spreadsheet solver for PC (LINDO systems), Pentium III is used. The solver can handle a large number of variables. It can also automatically detect and solve the nonlinear model (such as model 1) by a built-in nonlinear heuristic solver.

The study focuses on comparing three LIP models (model 2, 3 and 4). Model 2 (standard LIP) has an advantage in terms of optimization time but only for small size-grids, 8x8 cells, while model 3 (buffer) shows potentials for larger-sized grids. Optimization times increase significantly in model 2 and 4 (blocks), but not in model 3 when more and more weights are put on the compactness against development costs. However, all models can finally reach a point at which each land use is allocated in one closed patch at reasonable costs and low development costs.

This method is applied in the case of the restoration of former lignite mining dump sites in As Pontes in Galicia, Spain. It aims to design an optimum restoration plan that complies with European legislation. That means the mining area needs to be restored as close as possible to its pre-mining situation while meeting the legal requirement at the lowest cost. The spatial compactness objective in this case is to create large-closed patches of forest and water areas. The area is divided into 300x300 grid cells (25 m^2 per cell). The constraints that refer to as the legal requirement are defined by using Landsat TM images acquired before mining exploitation, i.e. 60% forest, 22% shrub and 18% water. The restoration costs are calculated by the functions involving elevation and slope factors derived from remote sensing data. Note that the factor parameters vary depending on land use types.

The results show the impossibility of the techniques to solve the LIP models for the whole site study area in one run. While Aerts and Heuvelink (2002) show successfully optimizing NLIP models using simulated annealing, for large integer variables set of 300x300 grid cells which is applied to a similar case study, as Aerts, et al. (2003a).

Nevertheless after many test runs, Aerts, et al. (2003a) obtain the success of model 3 with the area of 30x30 cells. The optimization time is around 2 minutes when a single objective of development costs is applied. But it takes more than 8 hours when the compactness objective is also integrated because of the hardware limitation in dealing with the relatively large number of integer variables (9,600) and constraints (57,855).

Aerts, et al. (2003b) convince that the combined optimization-GIS is a powerful method for land use allocation problems. A nonlinear GP model is formulated to solve the MLUA problem applied in the case of Jisperveld in the Netherlands where there is a debate on how to plan and manage the area as a consequence of the change in governmental land use planning policy from predominantly agriculture to a combined agriculture-nature area. The large closed patches of land use such as extensive agriculture and water limited access area, which are new types of land use in that area, represent higher natural and recreational values than the fragmented areas. Other types of land use in consideration are intensive agriculture, residence, industry, recreation sites and wetlands.

The optimization problem in this case involves the trade-off objectives of maximizing compactness and minimizing land development costs (as same as Aerts, et al., 2003a). The optimization model defines the decision variables as grid cells where the only one land use type can be specified in each cell. Therefore, the decision variables are binary numbers "0" or "1" as IP models presented by Aerts, et al. (2003a) and Aerts and Heuvelink (2002). The spatial constraints are the lower and upper bounds of the numbers of grid cells for each type of land use. Additional constraints are the fixed areas (the areas do not allow to be changed).

The generalized GP approach is used to define goal or reference point. Then, the GP model is formulated by using scalarizing functional form. It attempts to minimize the sum of deviations of both goals relative to the ideal value rather than the goal targets. The advantages of the approach are: it avoids the use of preference weights and the function is scale free. The application of simulated annealing is used to solve the model.

The results showed that when the weights on the compactness goals are set to twice the value for the weights on the cost objectives, the values of the spatial objectives improve (larger cluster). On the other hand, the costs of land use development increase and the natural and recreational values decrease. However, both the spatial values and natural and recreational values increase when the weight is set to a specific land use, i.e. the water area.

To sum up, the review above indicates the capabilities of GIS techniques when integrated in land use optimization problem with multiple objectives. The advanced frameworks, solving methods, and software are being developed. The summary of the above review is in table 2.

Table 2. Selected case studies of integrated optimization-GIS with land use allocation problem

Catagories	Grabaum and Meyer (1998)	Aerts, et al. (2003a)	Aerts and Heuvelink (2002)	Aerts, et al. (2003b)
Optimization models/approaches and solving techniques	LP and GP models/ loose coupling strategy	LIP models with preference weighting (goal-LIP); exact approach	NLIP models with preference weighting (goal-NLIP); heuristic approach-simulated annealing	NLIP models with preference weighting (goal-NLIP); heuristic approach-simulated annealing
Application: study area and problem statement	Land use options under various weight of goal functions in 48 km^2 landscape in Saxony, Germany	The restoration plan for former mining dump site, 2.25 km^2 (300x300 cells) of As Pontes in Galicia, Spain	As same as Aerts, et al. (2003a)	Requirements for maximum large-closed-patches of land use and minimum land use change costs in the case of Jisperveld, the Netherlands
Objective functions	Max. ecological regulations (soil erosion protection; water discharge; groundwater regeneration) and agricultural production	Min. land development costs; max. compactness objective (2 different compactness objective forms are formulated: a minimum number of buffer cells or blocks).	Min. land development costs; max. compactness objective	Min. land development costs; max. compactness objective
Decision variables	Land use types within polygons in terms of land areas; total numbers of variables equal to (1,729+146 polygons)x 3 land use options	Binary variable value, 0 or 1, is assigned in a particular grid cell for each land use type	Binary variable value, 0 or 1, is assigned in a particular grid cell for each land use type	Binary variable value, 0 or 1, is assigned in a particular grid cell for each land use type

Table 2. (Continued)

Catagories	Grabaum and Meyer (1998)	Aerts, et al. (2003a)	Aerts and Heuvelink (2002)	Aerts, et al. (2003b)
Constraints	i.Areas of polygons ii.Lower and upper limit of each land use type	i.Only one land use must be assigned in each cell ii.The required area proportions of land use as lower-upper bound iii.Same land use of neighboring cells or buffer cells or block	i.Only one land use must be assigned in each cell ii.The required area proportions of land use as lower-upper bound	i.Only one land use must be assigned in each cell ii.The required area proportions of land use as lower-upper bound iii.Fixed areas for specific types of land use iv.Minimum cluster size (area)
Optimization software	PC-DOS based LNOPT	"What's Best!" ,the spreadsheet solver for PC (LINDO systems)		
How GIS is integrated?	i.Loose coupling strategy ii.MCE-GIS to assess goal function values (used as coefficients in optimization model) and developing of the optimization land use maps	i.Spatial design technique ii.Applying grid-based land use allocation techniques	i.Spatial design technique ii.Applying grid-based land use allocation techniques	i.Spatial design technique ii.Applying grid-based land use allocation techniques
GIS software	Arc/Info			
Main results	Changing of actual land uses to optimum land use plan	Technical problem make the solving of large models like 300x300 cells impossible. The max. 30x30 cells can be solved within reasonable solution time—2 minutes only when the development cost is optimized. If both goals are optimized, it takes more than 8 hours.	Simulated annealing is capable of solving large spatial data sets of 300x300 grid cells and can handle nonlinear functions.	The effects of various goal weightings on land use options and land use development costs.

5. Conceptual Framework of CLU Optimization

The review of methods and cases above contribute to this section which describes the conceptual framework of MP model formulation for CLU problem. This section also explores some crucial points associated with the application of the model.

CLU problem solved by MP methods requires three basic characteristics. First, there is a scarce resource that restricts the uses involved in CLU decision process. Second, there is an economic decision to be made on which option is the best land use scheme amongst various alternatives of competing land uses based on the identifiable objective(s) and given restrictions. Third, the situation of such a problem can be quantified in some ways.

The first two characteristics are attached to each other and must be completely identified and represented as a mathematical model when optimized. To do so it requires a large number of information and numerical data derived from external procedure of MP. The data sets are used in model formulation as model inputs. The availability and the reliability of data play a great role on the model formulation and the results.

In applying MP to CLU problem, there are crucial key points to be considered. These are the identification of decision variables involved in the problem, the selection of an appropriate MP approach, the setting of optimizing objective(s) or goals in correspondence with the problem and the MP approach, the identification of constraints, and the seeking of an appropriate computer software to solve the model. The details are shown in table 3.

In addition, the review of applied GIS in section 4 presents the capability of the techniques to be integrated with MP in many ways. More application frameworks to CLU should be explored.

Table 3. The general framework of MP for CLU problem optimization

Key Points	**Identification**
Problem	The evaluation of the competing CLU situation and conflict problems is required. The details on the problem characteristics to be optimized can then be identified.
Decision variables	CLU sectors and activities involved in the problem must be clearly designated.
MP approaches	Select whether single-criterion approach or multi-criteria approach fits the problem. Note that each of the approaches has its own technical advantages and pitfalls (see section 2). The comparison of the experimental models—model structures, data requirement, solving techniques, solutions amongst different approaches and methods gives an extensive idea that benefits to the construction of the most appropriate framework to CLU problem in question.
Optimization objectives/ goals	The identification of the objectives/ goals is a crucial process. They should closely represent the problem and elicit the social preferences. The process includes the quantification of the coefficients. Several examples of promising objectives and goals are: -Economic efficiency: maximize present value of net social benefit (Kantangkul, 2000 and Araneda et al., 1996 internalized environmental values and externalities in objective function coefficients) or based on TEV approach (Bell and Cruz-Trinidad, 1996) -Natural environment and biology: environmental standard requirement, carrying capacity level, maintaining if environmental quality (see samples in table 1) -Sociology and legal: equity of resource use; basic need requirements; laws and policies (see samples in table 1)
Constraints	The identification of constraints includes the quantification of all parameters. The categories of potential constraints are: -Physical constraints, e.g. land suitability and availability, labor and capital availability, etc. -Ecological and environmental constraints (see Kantangkul, 2000; Chang et al., 1995) -Sociological and legal constraints—none of the cases in single-criterion approach as reviewed above applied these constraints. However, they are formulated as goals in several cases (see samples in table 1).
Computer software	The availability and suitability (capability and capacity to solve the model) of software is concerned. The examples of packages in solving LP, GP and MOP are GAMS (see manual in Brooke et al., 1998), MS Excel, LINDO, etc.

6. Conclusion

There is a large number of literature showing the contributions of MP to theoretical and methodological development. However, the main concern of this paper is to focus on its applications. MP has been applied widely in various fields especially in management science and operations research. In natural resources, numerous studies have been conducted, mostly in forest and water resources including land use planning, nonetheless, the work and literature related to MP's application to CLU problem are limited.

Improper uses of coastal land cause negative impacts on the coastal ecosystems and other vulnerable natural resources, which often erupt into conflicts among resource users and with other stakeholders. The consequences cannot be ignored and should be fully taken into account in the model. This makes the application of MP to CLU more complicated than other general cases of land use. For instance, the economic valuation is indispensable if the environmental values as consequences of land use alternatives are considered. They can be internalizing in the optimization model through the model objective(s) and/or constraints.

From the theoretical and technical points of view, the main advantages and disadvantages amongst three MP methods—LP, GP and MOP can be summarized as follows: Although LP requires less information than GP and commonly gives efficient solution, it can deal with only one objective, subject to rigid-tecinical constraints. This makes LP unattractive since the problems in natural resources always involve multiple and sometimes conflicting objectives. GP and MOP have advantage on this aspect in that they can deal with a problem that has more than one objectives or goals.

Although GP is efficient in term of computational time (the solution can be generated within a single run), it requires a large amount of information on goal targets, weights and pre-emptive priority levels from the DMs. On the other hand, MOP does not require such information but it rather provides the information through a set of efficient solutions. In addition, GP has high possibility to yield inferior solutions while MOP is purposed to eliminate the inferior solutions. Nevertheless, a large MOP model with more than 3 objectives can be difficult to solve and sometimes gives too large a set of efficient solutions which can still make decision choices difficult. Thus, there is need for an extra process to enable the search for the best solution by the application of the compromising approach.

The complementary methods as well as the variants of MP have been well developed in many recent studies that also deal with the pitfalls and improve the computational results with less effort.

The review has no intention of ranking the superiority of one particular method over another. In fact, comparing the methods seems pointless but comparison of their capabilities gives a clearer idea of the strengths and limitations of each method. This can in turn facilitate the search for an appropriate approach to derive a realistic model that can represent closely the problem and can arrive at valid solutions.

Interestingly, the integrated MP-GIS technique and software available today does not only visualize the optimum solution but is also able to solve the problem inside the package. The higher level usage of the technique is for policy decision rather than mere information. That is, it can be used interactively while the decision-making process is operating. The capability of the techniques and software to be applied to natural resource problems in question should be further explored.

It should also be noted that traditional land use optimization models based on a single economic objective, i.e. economic efficiency, commonly excludes or ignores non-economic objectives, e.g. environmental objectives, social effects and so on. This paper attempts to provide a strong evidence that the new framework of applying MP to a CLU problem to serve sustainable management and planning strategy should be based on “multi-criteria integrative approach” in which both economic and non-economic criteria as well as environmental values are taken into consideration.

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Appendix I: Evolution of GP researches

The first idea of GP techniques is initiated in 1955 by A. Charnes, W.W. Cooper and R.O. Ferguson who present the deviation minimizing approach inherent in GP. While in 1951, they are of 2 papers presented by T.C. Koopmans; and H.W. Kuhn and A.W. Tucker contribute to the initiation of MOP problem (Romero and Rehman, 2003:8). However, the term GP is first used by Charnes and Cooper (1961) in linear programming textbook, which present a more complete formulation of GP and it is started as an extension of LP in order to solve unsolvable LP problems, e.g. infeasible LP problems. GP has received substantial and widespread attention since mid-1970s. In fact, it is the most widely use multi-criteria decision making (MCDM) technique since then (Ignizio, 1985; Schniederjans, 1995; Tamiz et al., 1998).

The large number of bibliography surveyed by Schniederjans (1995) who classifies 746 literature of case studies and applied methodologies of GP models during 1955-1994 into 4 categories: 1) integer GP model (found 4.7%), i.e. all integer GP, mixed integer GP and zero-one GP models; 2) nonlinear GP model (2.7%); 3) other specialized model (5.8%), i.e. fuzzy GP model, chance constraint GP model, etc.; and 4) WGP and LGP model, or combined methodologies (86.7%).[33] The applications are also categorized in many fields, i.e. agriculture, engineering, accounting, finance, marketing, economics, education, health care, government budgeting and international aspects. Top three largest number of literature cover 70.2 % of 746 literature is found in the areas of management (human resource management, management information systems and production and operation management), government (education and health care) and finance. The proportion of literature classified in area of economics and applied economics (agricultural and international economics) is only 4.4%, that is, 2 articles relevant to environmental and resource economics,[34] 2 articles in agri-

33 According to Management Mathematics Group, there is a survey reported that 22% and 64% of GP applications used WGP and LGP respectively.

34 One is “A Goal Interval Programming Model for Resource Allocation in a Marine Environmental Economics and Management” by Charnes et al. (1976) published in Journal of Environmental Economics and Management 3(4): 347-362 and the other is “Economic-Emission

cultural economics and the less (29 articles) in other economic subjects. The summary of the survey result follows.

Load Dispatch through Goal Programming Techniques" by Nanda et al. (1988) in IEEE Transactions on Energy Conservation 3(1): 26-39.

Summary of bibliographical survey of applied GP in various areas from 1955 to 1994 conducted by Schniederjans (1995)

Areas/Categories	Number of Literature and Citation Years	Areas/Categories	Number of Literature and Citation Years
Accounting	**38 (I-4; N-0; S-0; M-34)**	**Finance**	**110 (I-4; N-1; S-12; M-93)**
• Assets	4 (1984-1992)	• Acquisition Analysis	6 (1985-1992)
• Auditing	8 (1971-1990)	• Banking	10 (1975-1992)
• Balance Sheet	2 (1979-1988)	• Bank Portfolios	4 (1977-1987)
• Budgeting	11 (1963-1990)	• Bond Portfolios	3 (1985-1989)
• Control Systems	1 (1980)	• Capital Budgeting	19 (1969-1989)
• Cost	4 (1977-1993)	• Capital Flow	3 (1974-1985)
• Public accounting	2 (1973-1991)	• Credit Analysis	1 (1987)
• Taxes	2 (1971-1992)	• Divestiture	3 (1988-1991)
• Transfer Pricing	1 (1974)	• Financial Planning	15 (1971-1992)
• Others	3	• Finance/Production	1 (1969)
Agriculture	**61 (I-0; N-2; S-6; M-53)**	• Global Financial Plan.	7 (1982-1992)
• Aquaculture	6 (1978-1990)	• Insurance	5 (1974-1982)
• Economics	2 (1981-1987)	• Investment Planning	9 (1975-1987)
• Farming	17 (1980-1993)	• Managing Risk	5 (1985-1992)
• Forestry	21 (1973-1991)	• Mutual funds Portfolio	1 (1973)
• Land Management	2 (1988-1993)	• Portfolio Analysis	9 (1975-1993)
• Pest Control	2 (1990-1991)	• Others	9 (1975-1986)
• Ranching	5 (1978-1992)	**Government Sector**	**169 (I-7; N-4; S-7; M-151)**
• Regional Planning	1 (1988)	• Education	45 (1970-1993)
• Storage	2 (1983-1984)	• Health Care	40 (1973-1993)
• Others	3	• Allocating Resources	8 (1977-1991)

(Continued)

Areas/Categories	Number of Literature and Citation Years	Areas/Categories	Number of Literature and Citation Years
Economics	**29 (I-1; N-1; S-4; M-23)**	• Environmental Issues	13 (1975-1991)
• Exporting	1 (1986)	• Govt budgeting	1 (1983)
• Income Distribution	1 (1984)	• Military	12 (1979-1994)
• Industrial Dev.	2 (1978-1989)	• Police Allocation	3 (1979-1985)
• Municipal Planning	1 (1971)	• Policy Evaluation	3 (1970-1980)
• National Policies	7 (1972-1994)	• Policy compliance	1 (1977)
• Pollution	1 (1988)	• Postal Service	1 (1973)
• Regional Planning	4 (1979-1986)	• Prison Management	1 (1990)
• Resource Allocation	1 (1976)	• Social Issues	8 (1974-1988)
• Others	10	• Transportation	2 (1984-1985)
Engineering	**25 (I-1; N-2; S-1; M-20)**	• Urban Planning	7 (1972-1991)
• Automated system	1 (1986)	• Utility Management	2 (1983-1988)
• Design Problem	11 (1977-1987)	• Waste Management	4 (1989-1993)
• Feasibility Study	1 (1991)	• Water Resource Mgt.	20 (1973-1993)
• Production Process.	1 (1986)	**Marketing**	**27 (I-1; N-0; S-0; M-26)**
• Routing	1 (1990)	• Distribution Channels	2 (1983-1991)
• Reliability	5 (1983-1993)	• Marketing/Production	2 (1978-1979)
• Software Application	1 (1990)	• Market Segmentation	1 (1992)
• Others	4	• Media Planning	7 (1968-1992)

(Continued)

Areas/Categories	Number of Literature and Citation Years	Areas/Categories	Number of Literature and Citation Years
Management	**245(I-16;N-8;S-11;M-210)**	• Pricing	2 (1988-1992)
• Human Res. Mgt.	53 (1955*-1991)	• Product Development	1 (1990)
• Mgt. Info. System	20 (1973-1993)	• Purchasing	1 (1987)
• Product.&Operat.	172 (1969-1994)	• Retailing	2 (1983-1987)
International Context	**42 (I-1; N-2; S-2; M-37)**	• Sale Management	3 (1970-1990)
• Accounting	2 (1978-1984)	• Warranty Estimation	3 (1988-1993)
• Agriculture	9 (1981-1992)	• Others	3
• Economics	2 (1991-1994)		
• Engineering	1 (1984)		
• Finance	14 (1988-1992)		
• Government	10 (1978-1993)		
• Management	4 (1983-1993)		

Note: "I" (Integer Goal Programming); "N" (Nonlinear GP); "S" (specialized GP); "M" (weighted and/or pre-emptive model, or combined methodologies).

* By Charnes, A, W.W. Cooper and R.O. Ferguson. 1955. Optimal Estimation of Executive Compensation by Linear Programming, *Management Science* 1(2): 138-151, this article firstly presents the deviation minimizing approach inherent in GP.

The collection in 1994 is incomplete.

Appendix II: Sources of bibliography on MCDM/GP&MOP

1. White (1990): A bibliographical survey of MOP and GP applications during 1955-1986. 504 references are cited from 97 journals, some of which are in areas of natural resources and environment (70 references, 14%)—especially in areas of water and forest resources. The applications in area of land use are also found (10 references, 2%). One reference in area of coastal land and resources is cited (Shamir, M. J.Bean and A. Galiel. 1984. Optimal Annual Operation of a Coastal Aquifer. Water Resources Research 20: 435-444).

2. Schniederjans (1995): A bibliographical survey of GP in various areas from 1955 to 1994 is conducted (see brief review in appendix I). Nevertheless, none of literature is found in areas coastal resources.

3. Steuer, et al. (1996): A bibliographical survey of MCDM and relevant activities throughout the world. The survey examines 1,216 journal articles during 1987-1992 and 217 books including 143 conferences on MCDM.

4. Ehrgott and Gandibleux (2002): This book gives the state of the art surveys of GP and MOP mainly in theoretical and methodological aspects. In chapter 3 of total nine chapters, GP literature during 1990-2000 is presented. The evolution algorithms and multiple objective optimization are explored in charter 6.

5. International Society on MCDM: The website provides lists of bibliography—books, proceedings, journals, conferences' articles, reports, abstract database related to MCDM. Good collection and up-to-date.

6. Management Mathematics Group: The website recommends some GP resources. Brief information on recommended textbooks, pioneer articles as well as some links to tutorial and software library are available.

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12/00	Finn Olesen	*Om Økonomi, matematik og videnskabelighed - et bud på provokation*

13/00	Finn Olesen Jørgen Drud Hansen	*European Integration: Some stylised facts*
14/01	Lone Grønbæk	*Fishery Economics and Game Theory*
15/01	Finn Olesen	*Jørgen Pedersen on fiscal policy - A note*
16/01	Frank Jensen	*A Critical Review of the Fisheries Policy: Total Allowable Catches and Rations for Cod in the North Sea*
17/01	Urs Steiner Brandt	*Are uniform solutions focal? The case of international environmental agreements*
18/01	Urs Steiner Brandt	*Group Uniform Solutions*
19/01	Frank Jensen	*Prices versus Quantities for Common Pool Resources*
20/01	Urs Steiner Brandt	*Uniform Reductions are not that Bad*
21/01	Finn Olesen Frank Jensen	*A note on Marx*
22/01	Urs Steiner Brandt Gert Tinggaard Svendsen	*Hot air in Kyoto, cold air in The Hague*
23/01	Finn Olesen	*Den marginalistiske revolution: En dansk spire der ikke slog rod?*
24/01	Tommy Poulsen	*Skattekonkurrence og EU's skattestruktur*
25/01	Knud Sinding	*Environmental Management Systems as Sources of Competitive Advantage*
26/01	Finn Olesen	*On Machinery. Tog Ricardo fejl?*
27/01	Finn Olesen	*Ernst Brandes: Samfundsspørgsmaal - en kritik af Malthus og Ricardo*
28/01	Henrik Herlau Helge Tetzschner	*Securing Knowledge Assets in the Early Phase of Innovation*
29/02	Finn Olesen	*Økonomisk teorihistorie* *Overflødig information eller brugbar ballast?*
30/02	Finn Olesen	*Om god økonomisk metode* *– beskrivelse af et lukket eller et åbent socialt system?*
31/02	Lone Grønbæk Kronbak	*The Dynamics of an Open Access: The case of the Baltic Sea Cod Fishery - A Strategic Approach -*

32/02	Niels Vestergaard Dale Squires Frank Jensen Jesper Levring Andersen	*Technical Efficiency of the Danish Trawl fleet: Are the Industrial Vessels Better Than Others?*
33/02	Birgit Nahrstedt Henning P. Jørgensen Ayoe Hoff	*Estimation of Production Functions on Fishery: A Danish Survey*
34/02	Hans Jørgen Skriver	*Organisationskulturens betydning for vidensdelingen mellem daginstitutionsledere i Varde Kommune*
35/02	Urs Steiner Brandt Gert Tinggaard Svendsen	*Rent-seeking and grandfathering: The case of GHG trade in the EU*
36/02	Philip Peck Knud Sinding	*Environmental and Social Disclosure and Data-Richness in the Mining Industry*
37/03	Urs Steiner Brandt Gert Tinggaard Svendsen	*Fighting windmills? EU industrial interests and global climate negotiations*
38/03	Finn Olesen	*Ivar Jantzen – ingeniøren, som beskæftigede sig med økonomi*
39/03	Finn Olesen	*Jens Warming: den miskendte økonom*
40/03	Urs Steiner Brandt	*Unilateral actions, the case of international environmental problems*
41/03	Finn Olesen	*Isi Grünbaum: den politiske økonom*
42/03	Urs Steiner Brandt Gert Tinggaard Svendsen	*Hot Air as an Implicit Side Payment Arrangement: Could a Hot Air Provision have Saved the Kyoto-Agreement?*
43/03	Frank Jensen Max Nielsen Eva Roth	*Application of the Inverse Almost Ideal Demand System to Welfare Analysis*
44/03	Finn Olesen	*Rudolf Christiani – en interessant rigsdagsmand?*
45/03	Finn Olesen	*Kjeld Philip – en økonom som også blev politiker*
46/03	Urs Steiner Brandt Gert Tinggaard Svendsen	*Bureaucratic Rent-Seeking in the European Union*
47/03	Bodil Stilling Blichfeldt	*Unmanageable Tourism Destination Brands?*

48/03	Eva Roth Susanne Jensen	*Impact of recreational fishery on the formal Danish economy*
49/03	Helge Tetzschner Henrik Herlau	*Innovation and social entrepreneurship in tourism - A potential for local business development?*
50/03	Lone Grønbæk Kronbak Marko Lindroos	*An Enforcement-Coalition Model: Fishermen and Authorities forming Coalitions*
51/03	Urs Steiner Brandt Gert Tinggaard Svendsen	*The Political Economy of Climate Change Policy in the EU: Auction and Grandfathering*
52/03	Tipparat Pongthanapanich	*Review of Mathematical Programming for Coastal Land Use Optimization*