A multi-objective model for environmental investment decision making

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Abstract

Investment in landscapes to achieve outcomes that have multiple environmental benefits has become a major priority in many countries. This gives rise to opportunities for mathematical programming methods to provide solutions on where investments could be made on the landscape, to maximise multiple environmental benefits. The problem was formulated as a multi-objective integer programming model, with objective functions representing biodiversity, water run-off and carbon sequestration. We applied a multi-objective Greedy Randomised Adaptive Search Procedure (GRASP) as an evolutionary programming method to find solutions along the Pareto front. This allows the decision maker to explore trade-off’s between the objectives. A 142,000 ha case study catchment in eastern Australia was used to test the methodology and assess the sensitivity of the different and often competing environmental benefits.

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Environmental and natural resource management is now a major category of social expenditure. In Australia the government has funded a National Action Plan for Salinity and Water Quality and the Natural Heritage Trust (EA and AFFA \cite{1}), which targets biodiversity conservation integrated with sustainable natural resource management. These programs aim to improve the condition of Australia’s natural resources. They will attract expenditure of over AU$3.5 billion during the years of 1997 to 2007. The United States Department of Agriculture (USDA), natural resource conservation service (NRCS) programs have a total budget of $2723 million for fiscal 2006 (USDA \cite{2}). The creation of large environmental programs generally results from political processes. At this level a program is defined by a set of broad overarching objectives and a budget. Program design commences in earnest at the next level down. The task of program managers is to achieve the highest possible attainment of program objectives by selecting the optimum portfolio of projects.

A commonality emerging from environmental programs worldwide is the need for program managers to identify, select and implement activities which maximise attainment of multiple environmental objectives. This must be achieved within a budget constraint. The analytical tools required to support program managers in these tasks are lagging. There is a need for models, guidelines and analytic frameworks that can help decision makers resolve trade-offs and direct limited resources towards projects or regions where the expected environmental returns are greatest. As a result of...
Table 1
Partial list of important environmental attributes in Australia

<table>
<thead>
<tr>
<th>Environmental attribute</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Nutrient runoff into streams (N &amp; P)</td>
<td>kg/ha/yr</td>
</tr>
<tr>
<td>2. Contribution to stream salt loadings</td>
<td>t/ML/ha/yr</td>
</tr>
<tr>
<td>3. Soil erosion</td>
<td>t/ha/yr</td>
</tr>
<tr>
<td>4. Stream sediment loads</td>
<td>mg/L/yr</td>
</tr>
<tr>
<td>5. Water yield</td>
<td>ML/ha/yr</td>
</tr>
<tr>
<td>6. Carbon sequestration</td>
<td>t/ha/yr</td>
</tr>
<tr>
<td>7. Biodiversity</td>
<td>Species type, richness and abundance</td>
</tr>
</tbody>
</table>

In this need, we have formulated an environmental investment model as a multi-objective integer programming problem, with the aim of maximising environmental benefits within a budget constraint. The multiple objectives arise from the multiple environmental benefits that can arise when investing in a land parcel or, for the purposes of the work presented here, a land grid cell. Table 1 contains a list of typical environmental attributes that can be modified through investment in Australian landscapes. Some of these attributes are spatially explicit, in that the benefits (e.g. reduced nutrient run-off in water, increased biodiversity) of investment in one location may depend on investments and benefits arising in other locations.

The model could be solved as a single objective problem through a weighted summation of the individual objectives (Szidarovszky et al. [3]), which is the most common approach to mathematical programming models with more than one objective. However, the use of a multi-objective methodology that produces multiple solutions along a Pareto front, would allow a decision maker to consider the trade-offs in benefits between the objectives when selecting a solution. In this paper, we adapt the GRASP meta-heuristic to be a multi-objective method for finding the solutions along the Pareto front of the proposed multi-objective environmental investment model. The rest of the paper is organised as follows. Section 1 provides a literature review of landscape planning problems and past multi-objective optimisation methods applied to finding solutions to these problems. Section 2 introduces the multi-objective environmental investment problem. In Section 3 we describe the GRASP method applied. Whilst a computational comparison with alternative methods is not a focus in this paper, we do provide some justification for using the GRASP, based on the characteristics of the proposed model. In Section 4, we test the methodology using a case study of the coastal Nambucca Heads catchment in north-eastern New South Wales, Australia. We also conducted a sensitivity analysis of the trade-off in the environmental objectives, and looked at the impacts of applying the methodology to a two objective problem versus three objectives.

1. Modelling environmental investments

The environmental investment problem can be formulated as a knapsack integer-programming problem, where the multiple objectives are aggregated using multi-criteria analysis. For example, Hajkowicz et al. [4] use this approach to optimise landscape scale investments across New South Wales in Australia. Grabau and Meyer [5] develop a multi-criteria model to improve several environmental criteria (e.g. soil erosion, water discharge) and a production criteria. These and many other such models do not explicitly capture the spatial dependencies that occur in some environmental attributes. Spatially explicit models are in abundance in the literature, but have been developed mainly for similar “single objective” applications.

For conservation planning, many researchers modelled biodiversity using a measure of connectivity between land parcels (or grid cells) selected. Williams and ReVelle [6] and Clemens et al. [7] incorporated spatial connectivity into the formulation by specifying sets of grid cells that form reserve patches. McDonnell et al. [8] achieve strong connectivity by minimising boundary length around patches of grid cells selected for conservation. The method used in Aerts et al. [9] for a land use allocation problem, which we also use in this paper, maximises the number of adjacent grid cells that also undergo the land use allocation. This method is computationally efficient for large problems.

Multi-objective optimisation is not new to land use or conservation investment applications, particularly with competing objectives of profitability versus environmental sustainability. In terms of environmental investment decision
making, a bi-criteria knapsack model was applied by Jenkins [10] to the restoration of contaminated lightstation sites with the objectives of minimising a weighted summation of environmental benefits score and level of uncertainty of the assessment. Zhu and Dale [11] prioritise several criteria (slope, transport, land use, price) for effective natural resource and environmental management. Multiple goal programming is an alternative method, but requires achievable goals to be set by the decision maker. For the land use allocation problem, Aerts et al. [12] apply goal programming to achieve the desired goals in total cost and total land assigned for each land use option. Zander and Kachele [13] used multiple goal programming to determine land uses for farming land to promote sustainable development. None of these environmental or conservation applications showed exploration of trade-off’s between the objectives along the Pareto front. However it is not difficult to adapt the methods used in these applications to explore such trade-off’s. For goal programming, Deb [14, pp. 408–409], and Saad [15] provided examples.

Multi-objective methods for generating solutions along a Pareto front have increased substantially since the early 1990’s. The majority of methods are evolutionary or genetic algorithm based, and the reader is referred to Deb [14] for an extensive overview of such methods, and Matthews et al. [16] for an application to land use planning. While genetic algorithms are well suited to multi-objective optimisation due to using several solutions simultaneously, other meta-heuristics (based on local search) have been shown to outperform them on many combinatorial optimisation problems. Armentano and Arroyo [17] constructed a multi-objective tabu search and applied it to a bi-criteria flowshop problem. Simulated annealing was adapted for multi-objective optimisation by Suppapitnarm et al. [18] and tested on three different engineering applications. They claimed the results were comparable to a well developed multi-objective genetic algorithm.

2. The environmental investment optimisation model

In this study we develop a modelling system that invests in a set of land grid cells to undergo environmental improvement, so as to maximise a range of environmental benefits. A fixed budget means that not all land cells can receive investment, and the resultant model formulation is similar to a spatially explicit knapsack problem with multiple objectives. We assumed that a grid cell can either undergo a full environmental investment (e.g. convert to tree cover) or it does not undergo investment at all.

In order to predict the benefits of landscape treatment arising from the investment, it is necessary to develop what can be termed a treatment-response model (TRM). This links physical actions on the ground to endpoint environmental outcomes, for example the decrease in stream sediment discharge following revegetation. Developing TRMs for all attributes listed in Table 1 is difficult, requiring considerable expertise and datasets. Often measures are used to represent groupings of attributes. In this study three measures are used for environmental benefits: (1) travel time of water to a river or waterway; (2) habitat connectivity; and (3) carbon sequestration. Other environmental measures can be used as well, such as soil erosion. Travel time of water is the time taken for rainwater to travel from its point of contact with the land to a river or stream. It can be used (Cherkauer [19]; Omernick [20]; Lu and Yu [21]) as a representation of the environmental attributes 1, 2, 4 and 5 of Table 1, which are water based. It can also be used as an indicator of water quality responsiveness following revegetation (Randhir et al. [22]). Increasing aggregate catchment travel time will generally imply improved water quality and reduce nutrient runoff and salt/sediment loadings. While all objectives lead to environmental benefits, different combinations of grid cells may lead to different degrees of benefit arising for each environmental attribute in Table 1.

Let the location of a cell on the grid be represented by \(i \in I, j \in J\) where \(I\) is the location on the “Y” axis and \(J\) is the location on the “X” axis. The binary decision variables for the environmental investment problem are defined as:

\[
x_{ij} = \begin{cases} 
1 & \text{if grid cell at location } i, j \text{ goes under environmental investment} \\
0, & \text{otherwise.}
\end{cases}
\]

Let the solution \(X = \{x_{ij} \mid i \in I, j \in J\}\).

2.1. Objective for environmental benefits based on maximising travel time of water

The purpose of this objective is to quantify the total time of travel of pollutants in water (e.g. nutrients, salts, fertilizers, sediments) from each grid cell to the stream, river or waterway. A long travel time will lead to a slower and reduced
runoff of pollutants and greater absorption by the landscape. The calculation of travel time is based on a travel path (to the stream, river or waterway), which is calculated using a digital elevation map. It is also based on the slope of the landscape and the Manning’s roughness coefficient. A small roughness coefficient, such as that found in bare ground, urbanisation and agriculture, will lead to a short travel time. A large roughness coefficient, such as that found in forestry landscape and the Manning’s roughness coefficient. A small roughness coefficient, such as that found in bare ground, will lead to a long travel time. The Manning’s coefficient for different land uses can be found in Appendix A. Using the Kinematic Wave equation from Chow [23] and Randhir et al. [22], the travel time through cell located at \( i \in I, j \in J \) is

\[
D_{ij} n_{ij}^{0.6} / (r_{ij} L)^{0.4} s_{ij}^{0.3}
\]

where \( n_{ij} \) is the Manning’s roughness coefficient for the cell at \( i \in I, j \in J \), \( L \) the travel distance along the flow path, \( s_{ij} \) the decimal slope of the cell at \( i \in I, j \in J \), \( D_{ij} \) the distance travelled through the cell at \( i \in I, j \in J \), \( r_{ij} \) is the rainfall excess rate (mm/s) at the cell located at \( i \in I, j \in J \), \( R_{ij} \) the travel path of sequence of cells from cell located at \( i \in I, j \in J \) to catchment outlet.

Accounting for environmental investments in some cells, the travel time (overland component) of water from the cell at \( i \in I, j \in J \) to the waterway (river or stream) is

\[
T_{ij} = \sum_{l \in I} \sum_{m \in J} \sum_{i, m \in R_{ij}} D_{lm} \cdot ((1 - x_{lm}) \cdot n_{lm} + x_{lm} \hat{n}_{lm})^{0.6} / (r_{ij} L)^{0.4} s_{lm}^{0.3},
\]

where \( \hat{n}_{lm} \) is the Manning’s roughness coefficient for the cell located at \( l = I, m = J \) if the cell undergoes environmental investment.

In the above expression for \( T_{ij} \), an environmental investment in cell \( l \in I, m \in J \) \( (x_{lm} = 1) \) would lead to an increase in the Manning’s roughness coefficient \( (\hat{n}_{lm} > n_{ij}) \) which would increase the travel time from cell \( i \in I, j \in J \) to the waterway, if water flows through cell \( l \in I, m \in J \) on the way to the waterway. The objective function is to maximise the travel time from all grid cells on the landscape to the waterway:

\[
f_1(X) = \sum_{i \in I} \sum_{j \in J} T_{ij}.
\]

2.2. Objective for environmental benefits based on biodiversity

It is commonly known in the conservation literature that biodiversity and persistence of species is increased with greater connectivity between cells undergoing investment (Onal and Briers [24] and Urban and Keitt [25]) or connectivity between cells undergoing investment with cells already committed to conservation (Margules et al. [26] and Williams and ReVelle [27]). Biodiversity is also improved with environmental investment that increases connectivity between existing conservation reserves or increases the size of the existing reserves.

A non-linear objective function that measures connectivity was used, similar to that in Aerts et al. [11]:

\[
f_2(X) = \sum_{i \in I} \sum_{j \in J} x_{ij} (x_{ij-1} + x_{i-1j} + x_{i+1j} + x_{ij+1} + \frac{1}{\sqrt{2}} (x_{i-1j-1} + x_{i+1j-1} + x_{i+1j+1} + x_{i-1j+1})).
\]

If a grid cell at \( i \in I, j \in J \) is committed to environmental investment \( (x_{ij} = 1) \), expression (2) is increased if the adjacent grid cells are also committed to environmental investment. The \( 1/\sqrt{2} \) factor accounts for the diagonally adjacent cells having a centre \( \sqrt{2} \) times the distance from cell \( i \in I, j \in J \), compared to the other adjacent cells. At a landscape level, expression (2) is maximised when grid cells committed to environmental investment are adjacent to one another to form a small number of large reserves.

2.3. Objective for environmental benefits based on carbon sequestration

To calculate carbon sequestration potential from land use change or environment investment, models are available to estimate the response. An approximation of response time to re-vegetation is the steady state carbon turn-over rate. A spreadsheet model was developed by the New South Wales (NSW) Department of State Forests, NSW Department of Land and Water Conservation and the CRC for Greenhouse Accounting (described in Montagu et al. [28]) which shows the carbon change over 10 years resulting from land use changes such as environmental investment. We used
the NSW model to produce the carbon sequestration benefits (measured in t/ha/yr) from an environmental investment for the case study in this paper. The data requirements for the NSW model are:

- Geo-referenced carbon measurements.
- Soil bulk density, soil depth, hydraulic conductivity.
- Climate data: monthly radiation, rainfall, max and min air temperature.
- Pre-European vegetation cover: growth form, species composition, canopy cover of tallest stratum.

We let $t_{ij}$ be the carbon sequestration benefit (t/ha/yr) from an environmental investment in the grid cell at $i \in I$, $j \in J$. Considering all grid cells, the objective function is

$$\text{Max } f_3(X) = \sum_{i \in I} \sum_{j \in J} t_{ij} x_{ij}. \quad (3)$$

2.4. Constraints

The total cost needs to be less than the budget:

$$\sum_{i \in I} \sum_{j \in J} c_{ij} x_{ij} \leq B, \quad (4)$$

where $B$ is the total budget of investment, $c_{ij}$ the cost of investment in grid cell at location $i \in I$, $j \in J$.

3. A multi-objective GRASP heuristic

In this section, we adapt the GRASP (Feo and Resende [29]) as a multi-objective optimisation method for finding solutions along the Pareto front to the spatially explicit environmental investment problem. The general GRASP is a multi-start process with a constructive and search phase. The constructive phase produces a feasible solution and the local search phase provides an improved solution. If this improved solution meets a set of criteria, it is added to the population. In implementing the GRASP, one needs to consider: the greedy method used; randomisation characteristics; the neighbourhood of the problem; intensification/diversification features; and the stopping criterion. There has been various intensification and diversification features added to the general GRASP to improve its performance, such as path re-linking (Resende and Ribeiro [30]), reactive GRASP (Delorme et al. [31]), hybrids and variations of the greedy construction method (Robertson [32]).

There were several motivations for using the GRASP method as follows. The single objective GRASP is a well known method for searching a wide solution space in difficult combinatorial optimisation problems that are prone to deep local optimal solutions (Laguna et al. [33]; Feo et al. 1994 [34]). The environmental investment problem is also prone to deep local optima because of its strong spatial relationships between decision variables, particularly in objective (2). Some specific applications of GRASP include flight scheduling and maintenance base scheduling (Feo and Bard [35]), the multi-dimensional assignment problem (Robertson [32]), and the set packing problem (Delorme et al. [31]). The latter has some similarities to the environmental investment problem of this paper in terms of selecting a subset of items (or grid cells) to maximise total value, given some constraints on the items selected. The environmental investment problem proposed in this paper has complicated objectives and potentially a large number of decision variables, compared to many other multi-objective applications. It is important for the decision maker to find solutions close to the Pareto front. The environmental investment problem is an extension of the bi-criteria knapsack problem and methods based on greedy or local search (features of GRASP) have been available in the literature (e.g. Hifi and Michrafy [36] and Cho et al. [37]) for finding good solutions to knapsack problems within a short CPU time. Methods using local search have also been applied to the bi-criteria knapsack problem such as tabu search (Gandibleux and Freville [38]) and scatter search (Gomes da Silva [39]). The claimed success in these papers along with simulated annealing in Suppapitnarm et al. [18] was a motivator for applying another meta-heuristic based on local search such as the GRASP in this paper.
Whilst the spatially explicit objectives represented by (1) and (2) can be CPU intensive to evaluate for a large number of decision variables, they are easy to update in a method based on local search that uses the add/drop and swap neighbourhoods. If a solution is modified using one of these neighbourhoods, the marginal change to the objectives can be calculated quickly without having to re-evaluate (1) and (2) for all decision variables. This makes the proposed construction and intensification phases of the GRASP very efficient. When using evolutionary methods based a crossover operator, (1) and (2) would need to be evaluated for all decision variables to produce a new solution.

When adapting the GRASP to the multi-objective model of this paper, the aim was to develop a population of solutions as close as possible to the Pareto front. The Pareto front is the set of non-dominated solutions where a solution \( X_a \) dominates \( X_b \) if \( f_k(X_a) \geq f_k(X_b) \) \( \forall k \) and \( \exists k : f_k(X_a) > f_k(X_b) \).

At the construction phase of the multi-objective GRASP, a solution is produced using a greedy search heuristic. Within the greedy search, a weighed summation objective, \( F(X) = w_1 f_1(X) + w_2 f_2(X) + w_3 f_3(X) \), was used where \( w_k \) is a randomly generated weight of objective function \( k \). A new set of randomly generated weights are used each time a solution is produced in the construction phase. Producing solutions using different sets of weights will allow solutions to be produced along the Pareto optimal front. The greedy search used is highlighted in the following algorithm:

**Algorithm 1.** Greedy search

Produce initial solution by randomly selecting grid cell locations \( i \in I, j \in J \) for environmental investment, until constraint (4) is reached. Let this solution be \( X \)

\[
\text{SET } X_{\text{best}} = X
\]

**REPEAT**

Select a sample of solutions from the neighbourhood of \( X \) and let \( X^\# \) be the solution with the largest \( F(X^\#) \).

Replace \( X \) with \( X^\# \)

IF \( F(X) \geq F(X_{\text{best}}) \) SET \( X_{\text{best}} = X \)

**UNTIL** Stopping Criterion

The stopping criterion used in the above greedy algorithm is an upper limit on the number of iterations without any improvement in \( X_{\text{best}} \). The larger the upper limit, the greater the likelihood a better local optimal solution will be found, but at the expense of increased CPU time. For the case study of this paper, we set the upper limit to 25 iterations without improvement in \( X_{\text{best}} \). The two natural neighbourhoods used for the environmental investment problem were:

- **ADD/DROP**: Add or remove a grid cell from the solution
- **SWAP**: Exchange the \( x_{ij} \) value of the two selected grid cells

The greedy search method in Algorithm 1 took sample of solutions from the neighbourhood (Semet and Taillard [40]), instead of searching the entire neighbourhood at each iteration. This has two benefits. It reduces the computational burden associated with a large neighbourhood, particularly as the environmental investment problem has a large number of decision variables. It also provides a randomisation feature into the greedy search. The performance of the greedy search and the overall multi-objective GRASP was sensitive to the size of sample used. To find a suitable sample size, we experimented with seven different sample sizes between 100 and 10,000 using ten runs of the greedy search (with a fixed \( w_1, w_2, w_3 \)) applied to the case study instance of this paper. We found, a sample size of 1000 for both the ADD/DROP and SWAP neighbourhoods was found to give the maximum \( F(X) \), but this depended on the desired CPU time limit for the multi-objective GRASP. The greedy search in Algorithm 1 allows non-improving moves to avoid many local optimal solutions. From a GRASP perspective, this effectively adds the local search phase to the construction phase.

In construction a set of solutions along a Pareto front using a multi-objective GRASP, there is a need to ensure diversity between solutions. One method is to apply a minimal distance criterion between solutions in the population. The distance measure used is based on the number of decision variables with differing values. For example, if \( X_a = \{ x_{ij} \} \forall i \in I, j \in J \) and \( X_b = \{ x_{ij} \} \forall i \in I, j \in J \) are two solutions, the distance between these solutions is:

\[
d = \sum_{i \in I} \sum_{j \in J} |x_{ij}^a - x_{ij}^b|.
\]

We let \( d_{\text{e}} \) = minimum distance of \( d \) between two solutions within the population. In the construction phase, a solution produced by the greedy search is only added to the population if satisfies the minimum distance criteria.
An intensification phase was added to the multi-objective GRASP. Its purpose in this paper is to search for potentially better solutions (or new non-dominated solutions) in the vicinity of the existing solutions in the population, and to search for better local optima that may exist between the existing solutions. We applied a method with similarities to path re-linking on a single objective GRASP (Resende and Ribeiro [30]), as a means of searching between two solutions. The method works by searching the solution space that exists between the solution produced in the construction phase and a solution randomly selected from the population. It incorporates the common features of the two solutions whilst searching for a better solution that may exist between them. If \( X \) is the solution produced in the construction phase and \( X_1 \) is a solution randomly selected from the population, a local search is applied to the difference \( (X, X_1) \).

The method exploration is described in Algorithm 2.

Algorithm 2. Path exploration

1. LET \( \tilde{X} \) be the set of cell locations \( i \in I, j \in J \) in the difference \( \Delta(X, X_1) \). That is, if \( X = \{x_{ij} \forall i \in I, j \in J \} \) and \( X_1 = \{x_{ij}^1 \forall i \in I, j \in J \} \) then \( \tilde{X} = \{i, j : x_{ij} \neq x_{ij}^1 \} \).
2. SET \( X_{\text{best}} = X \)
3. REPEAT
   a. Select a sample of solutions from the neighbourhood of \( X \) only considering cell locations in \( \tilde{X} \)
   b. Let \( X^# \) be the solution from the sample with the largest \( F(X^#) \).
   c. Replace \( X \) with \( X^# \)
   d. IF \( F(X) > F(X_{\text{best}}) \) SET \( X_{\text{best}} = X \)
4. UNTIL Stopping Criterion

As with Algorithm 1, the stopping criterion is an upper limit on the number of iterations without any improvement in \( X_{\text{best}} \). The multi-objective GRASP is shown in Algorithm 3, highlighting the main construction and intensification stages. The population of solutions constructed and maintained in the multi-objective GRASP contains non-dominated as well as some dominated solutions (construction stage), provided they are sufficiently different from other solutions within the population. Maintaining some dominated solutions added extra diversity in the population, particularly in regions of the Pareto front where there are very few non-dominated solutions. Performing the path exploration algorithm with a dominated solution may lead to a non-dominated solution being produced. As the population evolves after a large number of iterations, new solutions will replace dominated solutions and the population will evolve towards the optimal Pareto front. The stopping criterion is a CPU upper limit defined by the user, after which the remaining dominated solutions are removed from the population to give the Pareto front.

Algorithm 3. Multi-objective GRASP

1. REPEAT
2. CONSTRUCTION—Obtain a solution using a greedy search:
   a. Randomly select values of \( w_k \), s.t. \( \sum_k w_k = 1 \).
   b. Apply the greedy search algorithm to find a solution using the objective \( F(X) = w_1 f_1(X) + w_2 f_2(X) + w_3 f_3(X) \).
   c. Accept the new solution \( X \) into the population if:
      i. It is non-dominated.
      ii. It is dominated whilst dominating at least one solution in the population, and is at least \( d_e \) different to any solution in the population. The solution dominated by \( X \) with minimum \( d \) is replaced by \( X \)
3. INTENSIFICATION—Path exploration
   a. Randomly select a solution \( X_1 \) from the population with at least distance \( d_e \) from solution \( X = \{x_{ij} \forall i \in I, j \in J \} \).
   b. Apply the path exploration algorithm using weights \( w_1, w_2, w_3 \) from Step 1.
   c. Accept the new solution if not dominated by any in the population
      i. Remove the dominated solution in the population (if it exists) with minimal \( d \) to this new solution.
4. UNTIL Stopping Criterion.
5. REMOVE all dominated solutions from the population.
Whilst the greedy search of Algorithm 1 uses a weighted summation approach, Algorithm 3 overcomes many of the difficulties highlighted in Deb [14, pp. 54–55] of the classical weighted summation approach. One of the difficulties highlighted by Deb [14] (which is a potential issue in the case study of this paper) was that an even spread of weights does not necessarily lead to an even spread of solutions on the Pareto front. In Algorithm 3, the features of repeatedly randomly generating weights linked with dominance criteria and the feature of path exploration, allow the exploration along the Pareto front in regions that are highly sensitive to small changes in weights. In particular, if there is a gap of solutions along the Pareto front, the path exploration feature will search for non-dominated solutions between solutions at either side of the gap. The biggest disadvantage of the weighted summation method highlighted by Deb [14] is difficult with non-convex problems. If points A and B are two solutions on the Pareto front, and the Pareto front is non-convex between these solutions, the path exploration feature will still provide a search for non-dominated solutions in-between these solutions. However, we do not know the computational efficiency on non-convex problems compared to popular multi-objective evolutionary algorithms such as the non-dominated sorting genetic algorithm (Srinivas and Deb [41]) and the strength Pareto evolutionary algorithm (Zitzler and Thiele [42]), since the case study of this paper appears convex (at least in a two objective case).

4. Application to a case study catchment

The Nambucca Heads catchment is located in northeastern New South Wales (NSW) near the city of Coff’s Harbour in Australia (Fig. 1) and is used to illustrate the application of the methodology. It forms part of the Northern Rivers Catchment Management Authority, a statutory agency responsible for managing natural resources over a large part of northeastern NSW. Some of the major environmental hazards in the region include acid sulphate soils, soil erosion, stream sedimentation, high stream nutrient loads, weeds, urban development pressures and water use/availability. The catchment has high resolution land use mapping compiled from detailed aerial photographs, climate data and a digital elevation model. It has a mix of agricultural, urban and industrial landuses as shown in Fig. 2. The dominant agricultural landuse by area is livestock grazing.

To construct the model for the Nambucca case study, the region was partitioned 400 m by 400 m grid cells with 133 increments in \( i \in I \) and 148 increments in \( j \in J \). This meant there were 19,684 cells in total. Only land currently used for grazing or intensive agriculture could undergo environmental investment, which is about 3987 cells. To set up objective function (1), data were needed on digital elevation across the grid cells, from which the decimal slope \( s_{ij} \), sequence of cells to catchment outlet, \( R_{ij} \), and distance travelled could be calculated (Bui and Moran [43]). A table for the Manning’s roughness coefficient, \( n_{ij} \), is given in Appendix A. Costs, \( c_{ij} \), were randomly generated within
plausible ranges. The costs are based on an estimate of land values and revegetation costs. In a real application of the methodology, the costs would be the prices demanded by farmers/landholders for the proposed landscape treatments such as tree planting.

In applying the multi-objective GRASP method, algorithm parameters needed to be set, which required some experimenting to find values that appeared to work best for the case study. We used Eq. (5) for the distance between solutions, with $d_i$ being set to 8. This means that at least 8 decision variables needed to be different between two solutions. The methods was coded in Lahey Fortran 95 (v7.0) on a Pentium M 1.8 Ghz notebook computer with one gigabyte of RAM.

The model for the Nambucca case study has 3987 decision variables of $x_{ij}$, as this is the number of land cells eligible for investment. This number of decision variables, along with the spatial dependencies, makes it a large problem for multi-objective optimisation where multiple solutions are produced and maintained. A CPU time of 18 h was required given the problem size and parameters for the solution methodology. A short CPU time is not required since the model is used for strategic planning.

In the first test we only used objectives (1) and (2), and the Pareto front of 219 non-dominated solutions are contained in Fig. 3. The solutions were quite evenly spread though there were more solutions for small $f_2(X)$ compared to large $f_2(X)$. Large values of the connectivity objective, $f_2(X)$, requires a highly connected grid cells in the solution (i.e. a small number of large conservation reserves), due to the strong spatial dependencies in the decision variables. Depending on the initial solution, there is often the need for the multi-objective GRASP to overcome very deep local optima to produce solutions of large $f_2(X)$. For example, a solution with two connected reserves will likely have a larger $f_2(X)$ than a solution with three connected reserves. To convert the solution with three reserves to two reserves, the multi-objective GRASP needs to set the decision variables $x_{ij}$ to 0 for the grid cells in one of the reserves (thus removing the reserve) and expand the other two reserves subject to the budget constraint. A large number of non-improving moves will be needed to achieve this.

The two elite solutions (i.e. solution with largest $f_1(X)$ and $f_2(X)$) are presented in Fig. 4. With a travel time of water objective only (i.e. largest $f_1(X)$), the areas for investment tended to be spread out with some connectivity in
the form of strips (or barriers), which act as a means of slowing down water run-off to the catchment outlet. This type of pattern was expected when validated against the travel time analysis in Randhir et al. [22], and is very different to the investment plan for the connectivity objective. The connectivity objective led to a small number highly connected patches to be formed, which is a consistent pattern with modelling work in Clemens et al. [7] and Schadt et al. [44] for habitat reserve designs.
In the second test all three objectives were used. As with the two objective example, a total CPU time of 18 h was used. When using three objectives, 918 non-dominated solutions were produced. This is considerably more than the 219 produced in the two objective case and was due to the ease of finding more non-dominated solutions in a 3-D Pareto front vs. a 2-D one. **Fig. 5** shows the Pareto front for this three objective test. Due to the increased difficulty of effectively displaying a front with three objectives, three different graphs were used showing a trade-off of two objectives at a time. This also allowed a comparison to be made to the two objective case of **Fig. 3**. Where there appears to be dominated solutions in each of the three graphs of **Fig. 5**, these solutions were non-dominated when considering the objective not displayed in that graph. In **Fig. 5**, the trade-off in objectives appears more complex compared to the two objective example. Only the trade-off between carbon sequestration and connectivity produced a clear convex trade-off. The trade-off between “time of travel for water run-off” and “connectivity” was considerably different in the three objective case compared to the two objective case in **Fig. 3**, particularly for low values of “connectivity”. Another observation was that including carbon sequestration as an objective made it difficult to produce solutions with large environmental benefits in terms of “time of travel for water run-off”, and is possibly the reason for losing convexity in **Fig. 5**. In **Fig. 5**, there were no solutions with \( f_1(X) > 22,000 \), whilst about 40% of the solutions in **Fig. 3** were greater than 22,000. This highlights the high sensitivity of environmental benefits based on “time of travel for water run-off” in multi-objective environmental decision making. The connectivity objective was not as sensitive when introducing the carbon sequestration objective since the range of values in \( f_2(X) \) were similar to that in **Fig. 3**. **Fig. 6** shows a 3-D representation of the objectives, which appears to display a more convex surface compared to the 2-D graphs of **Fig. 5**. The solutions were not evenly spread over the surface. For example, there were much fewer solutions produced with large \( f_2(X) \) than small \( f_2(X) \).

5. Conclusions and future developments

Environmental investment programs are multi-objective in nature because of the different types of benefits that can be achieved, from maintenance of biodiversity through to reducing nutrient run-off and carbon sequestration. Depending upon the decision makers (e.g. governments, natural resource management boards, regional councils) there
may be different priorities on environmental benefits achieved, which is very much influenced by the local context of the landscape catchment in question. Instead of producing one single solution, it is desirable to consider a range of solutions along a Pareto front with trade-off’s between the different environmental objectives. We achieved this by constructing a spatially explicit integer programming model to represent the environmental investment problem with multiple objectives and applying a multi-objective GRASP to find solutions along the Pareto front.

The Nambucca catchment in eastern Australia was used as a case study to test the methodology and conduct an analysis of trade-off’s between the objectives. When applying the methodology to find a Pareto front in a two objective model, “connectivity” and “time of travel of water run-off”, the trade-off appeared convex with generally a good spread of solutions along the front, except for high levels of connectivity. However, adding the third objective in the model changed the Pareto front considerably. The trade-off’s between objectives appeared less complex, and solutions with large “time of travel of water run-off” environmental benefits (compared to the two objective case) were not able to be found. This showed the high sensitivity of a multi-objective environmental investment problem when adding additional objectives, and is an issue that needs to be addressed in further research.

In the near future we will also be developing a user-friendly front end to allow regional natural resource management bodies and government agencies to explore various investment plans using the model. A further development will be to adjust the model to work with land holdings/parcels rather than abstracted grid cells. This is because environmental investment plans in practice often involve land owners, who will implement the environmental decisions on their land parcels of various shapes and sizes.

**Acknowledgments**

The authors thank Dr David Hilbert and Dr Kristen Williams of CSIRO Sustainable Ecosystems, and the anonymous referees for their helpful input into improving the paper.
Table A1

Estimated values of Manning’s $n$ for given land use /land cover groups

<table>
<thead>
<tr>
<th>GRID_CODE</th>
<th>WN_LANDUSE_DESC</th>
<th>MANNINGS_n</th>
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<tbody>
<tr>
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<td>Unclassified</td>
<td>0.4</td>
</tr>
<tr>
<td>1</td>
<td>Water</td>
<td>0.02</td>
</tr>
<tr>
<td>2</td>
<td>Urban</td>
<td>0.015</td>
</tr>
<tr>
<td>3</td>
<td>Eroded areas or quarries</td>
<td>0.05</td>
</tr>
<tr>
<td>4</td>
<td>Airfield</td>
<td>0.013</td>
</tr>
<tr>
<td>5</td>
<td>Roads—Minor</td>
<td>0.02</td>
</tr>
<tr>
<td>7</td>
<td>Roads—Freeway</td>
<td>0.02</td>
</tr>
<tr>
<td>8</td>
<td>Roads—Highway</td>
<td>0.02</td>
</tr>
<tr>
<td>9</td>
<td>Roads—Major</td>
<td>0.02</td>
</tr>
<tr>
<td>10</td>
<td>Weir Walls</td>
<td>0.02</td>
</tr>
<tr>
<td>13</td>
<td>Plantation—Softwood old growth</td>
<td>0.6</td>
</tr>
<tr>
<td>14</td>
<td>Plantation—Softwood new growth</td>
<td>0.4</td>
</tr>
<tr>
<td>15</td>
<td>Plantation—Native vegetation</td>
<td>0.6</td>
</tr>
<tr>
<td>16</td>
<td>Plantation— Cleared or replanted</td>
<td>0.4</td>
</tr>
<tr>
<td>17</td>
<td>Moist pastures or cropping</td>
<td>0.1</td>
</tr>
<tr>
<td>18</td>
<td>Unimproved pastures</td>
<td>0.1</td>
</tr>
<tr>
<td>19</td>
<td>Heavily grazed pastures</td>
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</tr>
<tr>
<td>20</td>
<td>Bare ground</td>
<td>0.02</td>
</tr>
<tr>
<td>21</td>
<td>Bare ground</td>
<td>0.02</td>
</tr>
<tr>
<td>22</td>
<td>Vegetation—Forest and woodland</td>
<td>0.6</td>
</tr>
<tr>
<td>23</td>
<td>Vegetation—Rainforest</td>
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<tr>
<td>25</td>
<td>Vegetation—Wetland</td>
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<tr>
<td>26</td>
<td>Vegetation—Sparse</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Appendix A.

A table for the Manning’s roughness coefficient, $n_j$, is given in Appendix A (Table A1).

References


