Triple bottomline, hyper-radial-visualisation-based 'decision-making by shopping' for a land use management problem using evolutionary multi-objective optimisation

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Abstract. A land use multi-objective optimisation problem for a 1500ha farm with 315 paddocks was formulated with 14 objectives (maximising sawlog production, pulpwood production, milksolids, beef, sheep meat, wool, carbon sequestration, water production, income, and Earnings Before Interest and Tax (EBIT), and minimising costs, nitrate leaching, phosphorus loss, and sedimentation). This was solved using a modified Reference-point-based Non-dominated Sorting Genetic Algorithm (R-NSGA II) augmented by simulated epigenetic operations. The search space had complex variable interactions and was based on economic data and several interoperating simulation models. The solution was a Hyperspace Pareto Frontier (HPF), where each trade-off point represented a set of land-use management actions taken within a 10-year period and their related management options, spanning a planning period of 50 years. It involved as many as 3,150 integer variables with a number of soft constraints involving adjacency and other requirements of the land use problem. A trade-off analysis was achieved using Hyper Radial Visualisation (HRV) by collapsing the HPF into a 2-D visualisation capability through an interactive Virtual Reality (VR)-based method, thereby facilitating intuitive selection of a sound compromise solution dictated by the decision makers' preferences under uncertainty conditions. There was no perfect knowledge of uncertainty, despite taking account of epistemic uncertainty for some of the objectives. However, application of Bernoulli's Principle of Insufficient Reason or the Equal Distribution of Ignorance, reflected the aleatory uncertainty. Given the flexibility of trying different preferences and uncertainty conditions, the decision makers literally "shopped" for their preferred compromise decision or solution, allowing the method to be used as a "visual steering" capability. A 3-D trade-off visualisation that collapsed the 14 objectives into profitability, environmental and productivity composites gave the decision makers a sense of direction to steer. Four scenarios of the HRV were considered, one unbiased and the other three biased through preferences and values towards economic, sedimentation and nitrate leaching aspects respectively—giving rise to a triple bottomline (i.e., the economic, environmental and social complex, where the social aspect is represented by the preferences of the various stakeholders). The set of preferences for each scenario was determined through an iterative process with assistance from the 3-D trade-off visualisation for visual steering. A pairwise ranking for the four scenarios was then carried out with each decision maker submitting his/her own ranking, in an attempt to capture all their carefully considered preferences and values. The Multiplicative Analytic Hierarchy Process (M_{AHP}), which is devoid of the ranking irregularities common in most ranking methods, was used to determine the final compromise solution. Highlights of the approach are the development of an innovative epigenetics-based multi-objective optimiser, uncertainty incorporation in the search space data, and decision-making on a multi-dimensional space through a VR-simulation-based visual steering process controlled at its core by a MCDM-based process. This approach has widespread applicability to many other “wicked” societal problem-solving tasks.

Keywords: Evolutionary Algorithms, epigenetics, Reference-point-based Non-dominated Sorting Genetic Algorithm (R-NSGA II), Hyperspace Pareto Frontier (HPF), Triple bottomline, Hyper Radial Visualisation (HRV), Visual Steering, Multiplicative Analytic Hierarchy Process (M_{AHP}).

1. Introduction

This research originates from the recent land use management study [1] based on a farm in Rotorua, New Zealand. The farm property we considered is situated in a 9,065 km^2 region, Rotorua District, where the main economic sectors are tourism, forestry and agriculture. Rotorua District has many lakes, and there is a need to manage land use in order to balance utilitisation of commercial interests to preserve water quality. The largest of them, Lake Rotorua, is at the risk of eutrophication, toxic algal blooms, aquatic ecosystem stress and risks to human health. The major nutrient inputs include agricultural fertilisers, farm animal excretions, discharge from septic tank soak fields and urban runoff. Left unchecked, these nutrient inputs will ultimately mean the loss of tourism and recreation revenue, decrease of land values, etc. There are 20 problematic farms in the district, of which 15 are predominantly dairy farms and the remainder, predominantly dry stock farms.

Forestry and agricultural sciences are known to be the first sciences that investigated the critical effects of land use and large-scale human impact on the environment [2]. That investigation is central to sustainability issues or, more specifically, the triple bottomline—i.e., the balance between the environmental, economic (as in profitability and productivity) and social aspects. Therefore, pursuing sustainability in the Rotorua District will inevitably imply taking into account the preferences and values of different stakeholders in a bid to acquire robust social knowledge, but at the expense of introducing into the mix, social complexity or “wicked dynamics”. This investigation is transdisciplinary [3] as it defines a science area that amalgamates the traditional disciplinary and interdisciplinary scientific activities with social complexity, leading to new relationships between science and different parts of society. We demonstrate a transdisciplinary approach in this manuscript using a land use case study in Rotorua, New Zealand and highlight the fact that multi-objective optimization and multi-criterion decision-making concepts used in this problem can very well be extended to solve other similar and important societal problems.

Land use problems are examples of “wicked” societal problems [1], because a successful approach requires dealing with a multitude of factors (development costs, profitability over an extended time period, environmental and societal impacts), and choice among a huge number of possible alternative plans.

Because the societal impact factors are not possible to model and predict with any level of confidence, use of sophisticated decision-making tools may appear infeasible. However, the approach described here will use mathematical models to drastically reduce the size and complexity of the set of alternative plans to be considered, and then involve stakeholders "in the loop" to see that the societal concerns are addressed, without modeling them explicitly. A sophisticated, evolutionary multi-objective optimisation (EMO) algorithm is used to find the set of land-use plans that is worth further exploration, as it contains only plans that are close to being Pareto-optimal with respect to a set of 14 objectives including environmental impacts, productivity, and profitability measures. The virtual reality (VR) tools being developed are used by stakeholders to visualize and explore the tradeoffs to be considered between the conflicting environmental and economic impacts, thus introducing the societal element of the triple bottomline.

We highlight here that the outcome of this MCDM process was positive because the alternative solutions over which the process was conducted were all non-dominated solutions obtained by our proposed efficient multi-objective optimizer. Absent such non-dominated solutions, given that divergent preferences exist, then similar outcomes might well not be expected.

Figure 1 shows the entire approach that includes the modeling modules/ components. The first module articulates the interoperability of distributed simulation models that represent the system including collated data from the farm operations—especially expenditure and income. The information is then used to construct the search space, which is tailored to work with an evolutionary multi-objective search engine. This is the problem formulation stage, which involves design of the chromosome and the appropriate evolutionary algorithm to do the search. The epigenetic operator helps to decompose large search spaces into a series of smaller manageable searches for the evolutionary algorithm. The solution is a Hyperspace Pareto Frontier and via the virtual simulation tools the ranked alternatives are obtained by a combination of "decision-making by shopping", visualisation and Multi-Criterion Decision Making (MCDM).

The rest of this manuscript describes these processes and modules in more detail. A full account of the outcomes of the land use case study derived from application of this approach is outlined in the Results and Discussion section, followed by a brief discussion of future research aspirations and concluding remarks on the outcomes.

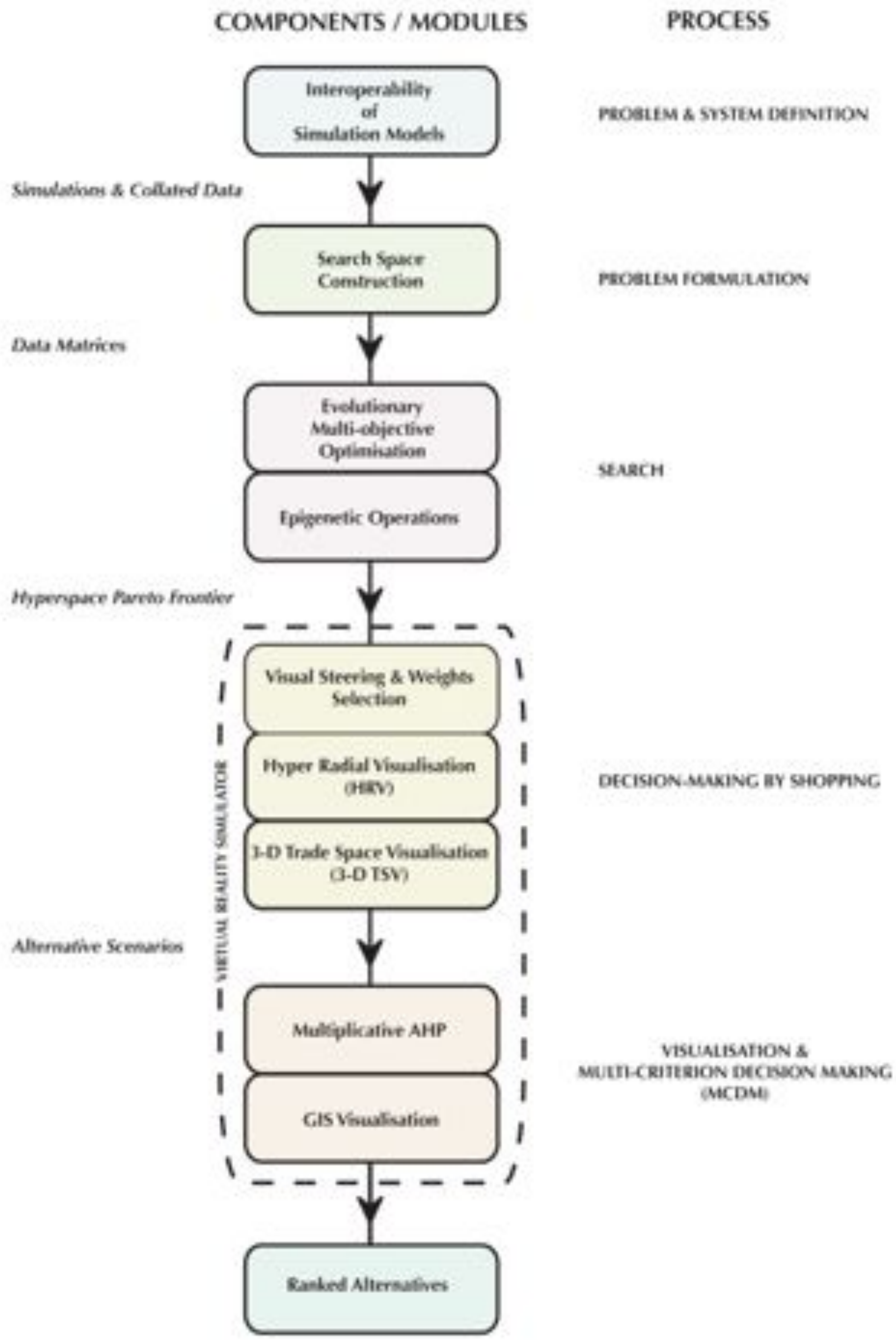

Figure 1. Modelling modules and their related processes i.e. problem and system definition, problem formulation, search, decision-making by shopping, and visualisation and Multi-Criterion Decision Making (MCDM).

2. Data and interoperability of simulation models

The pilot study is from our original research project [1], a farm owned by a NZ indigenous Maori Trust, which is 1,500 ha in size consisting of 315 land use paddocks, each potentially updatable to several different land uses – diary cattle, beef cattle, sheep, pine forest, etc. Under each land use were different management options with unique environmental and economic outputs.

Starting from the initial state, all 315 paddocks were allowed to change land use and/or management option at any one time over a 10-year period. For any given plan, 14 different objectives involving the production, costs and income from sawlog, pulpwood, milksolids, beef, sheepmeat (i.e. lamb and mutton), wool, and environmental factors such as emissions of carbon dioxide equivalents - CO_2e (which is negative for agriculture and positive for forests because of carbon sequestration), nitrate leaching, phosphorus loss, sedimentation, and water quantity from surface water runoff, were computed over a planning period of 50 years. The search space data for all of these objectives were built through the interoperation of different simulation models, such as STANDPAK [4] for Monterey pine growth and yield simulation, OVERSEER [5] for soil nutrient budget simulations under different farming systems, FARMAX [6] for simulating "what-if" scenarios for best pasture growth conversion to maximum profit for grazing animals, and so on. At this stage the interoperation is still manually set up, although in the future the investigators will develop/adapt a platform for simulation model interoperability, which will automate the generation of these search spaces, including trends and variances of costs, revenue and interest rates that will simulate real world uncertainties for a more robust optimisation.

For this current case study, we have simulated the trends for commodity prices, farm expenditure/costs, and interest rates for agriculture (i.e., sheepmeat (mutton and lamb), wool, beef and milksolids) and forestry (sawlog and pulpwood), which helped to minimise epistemic uncertainty for the 50 year-planning period. Depending on the extent of the time-series data points a commodity price trend was estimated using either genetic programming (GP) techniques [7] or Monte Carlo simulation techniques by determining moving minimums, averages, and maximums for a three-year window and using this information to simulate the commodity price trend with either a beta or triangular probability density function [8]. Model descriptions are given in Appendix A, where the GP models were determined using GPTIPS [9,10] running under MATLAB and the Monte Carlo models also estimated using MATLAB. The better of the two techniques was chosen for use in calculating each of our objective functions, based on their predictive ability.

3. Evolutionary Algorithms

The initial attempts to solve a large 14-objective optimisation problem a competitive co-evolutionary Multi-Objective Genetic Algorithm (MOGA) [1] running in the Genetic and Evolutionary Algorithm Toolbox (GEATbx) for MATLAB [11]. The program was terminated after 6 days of computation on a dual 6-Core CPU Mac pro desktop computer, without showing any signs of convergence. Combined with the *epigenetic* metaphor, the MOGA algorithm converged only partially. The Fonseca and Fleming ranking scheme in MOGA [12] used to determine the non-dominated solutions simply could not cope with the many objectives, losing diversity rapidly and determining Pareto points in limited sub-regions of the Pareto frontier.

3.1 The combined effect of genetic and epigenetic evolution

Genetic algorithms (GAs) may be customised to exploit the nature of a high-dimensional problem for a more effective and “intelligent” search of a space of potential solutions. Finding useful ways to decompose the problem space allows a simultaneous series of much smaller searches that are likely to produce globally optimal or near-optimal results in short computational times. The chromosome design and effective search technique for the GA was motivated by our observations of biological gene expression, an epigenetic process.

While biological genetic evolution is a slow process, epigenetic changes can occur much more quickly [13], and the combined effects of genetic and epigenetic changes can yield rapid changes in the final phenotypic outcome [14]. The success of an expressed phenotype is dependent on the combined effect of genetic and epigenetic evolution. While GAs were inspired by common operations in DNA sequence evolution, and applied successfully to solve many complex optimisation problems, we see an opportunity for computational gains without compromising the quality of a solution, by emulating gene expression in an evolutionary algorithm. We believe that many high-dimensional problems could benefit from such an approach. Also, a successful implementation of gene expression in evolutionary algorithms may lead to new biological insights [15], although this is beyond the scope of this manuscript.

For the land use problem, we considered gene regulation emulation at two levels, i.e., transcriptionally at a chromatin structure level via histone modifications and post-transcriptionally via RNA editing [16]. Instead of using MOGA, we modified the Reference point-based Non-dominated Sorting Genetic Algorithm (R-NSGA-II) [17], to accommodate an epigenetic metaphor. The reason for using R-NSGA-II rather than the popular NSGA-II was because R-NSGA-II replaces the crowding distance clustering algorithm in NSGA-II, which is good for two objectives, with a preference operator that uses the epsilon algorithm for a better trade-off search where there are more than two objectives. R-NSGA-II also enabled us to specify the reference points for the search where we were most likely to find solutions of interest. For this pilot study, the reference points were determined through trial and error by doing limited optimisation runs of 5-10 generations each.

The upper and lower bounds of the reference point vector used in R-NSGA-II were as follows:

Upper bound = [0, 12, 10, 3, 15, 5, 2, 1, 5, 1, 2, 0, 0, -5]; and

Lower bound = [-9, 0, 0, -25, 0, -2, -10, -30, -5, -15, -15, -15, -10, -30],

for the 14 objectives–water quantity, nitrate leaching, phosphorus loss, CO_2e, sedimentation, costs, income, EBIT, milksolids, sawlog, pulpwood, beef, sheepmeat, and wool, in that order.

We also used a low epsilon value of 0.001, which meant that we could only get a narrow spread of solutions near the reference points. A value of 0.01 would be considered large for this problem, meaning a large spread of the Pareto points near the reference points.

3.2 Multi-objective optimisation model

Formulation of the land use multi-objective optimisation was complicated by spatial (or more specifically, adjacency) constraints defined by the neighbourhood topology of GIS polygons representing the 315 paddocks. These constraints enable contiguous placement of common land uses and/or management options spatially, so that solutions with large contiguous blocks (as in amalgamation of several polygons) are preferentially obtained, for economies of scale [50]. These constraints can be handled in our proposed evolutionary search approach in different ways, which we discuss in Section 3.3 using a post-transcriptional epigenetic approach. Here, in this work, we treat these constraints simply as soft constraints and modify the objective functions so as to emphasize solutions having lesser violation of adjacency constraints. The land use optimisation problem in the presence of adjacency constraints makes the associated search *combinatorial* -- a problem normally dealt with by converting the GIS vector layer into a raster layer and using its regular cell or grid pairwise neighbourhood topology to define regular spatial constraints. The resulting problem is then solved using a classical approach, integer or mixed integer linear programming. Although such an approach is mathematically convenient for small problems, it is not efficient for larger combinatorial ones, as it becomes computationally prohibitive to exhaustively search the space.

The 14 fitness functions were based on the normalised data of the objectives, making them dimensionless and possible to trade off despite being incommensurable and sometimes conflicting. Four objective functions for any solution x ($obj_{i,t}(x)$, $i \in M$ (the set of indices for minimisation objectives) and t=1,2,…,50 years) were to be minimised, including sedimentation, nitrate leaching, phosphorus loss, and costs. Therefore, the transformed objective function for each of them is $f_{i,t}(x) = obj_{i,t}(x)$. The remaining ten fitness functions were to be maximised, including sawlog, pulpwood, milksolids, sheep meat, beef, wool, income, EBIT, water quantity, and CO_2e [1]. The maximisation objectives are converted to equivalent minimisation problems by multiplying the objective values by -1. Thus, the transformed objective function for each of them is $f_{i,t}(x) = -obj_{i,t}(x)$.

For the k-th population member, the 14 objective values ($f_{i,t}(k)$, i=1,2,…,14) are computed as a time-dependent function (for t=1,2,…,50) using the mathematical model described in Appendix A. Thereafter, a fitness function for the i-th objective for the k-th population member ($fitfunc_i(k)$) is derived from the time series expression of i-th objective function as follows and minimised:

$$Minimise\ fitfunc_i(k) = \left(1 + p(k)q_i\right)\left[\alpha \frac{1}{T}\sum_{t=1}^{T} f_{i,t}(k) + \beta\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(f_{i,t}(k) - f_{i,t}^{avg}(k)\right)^2}\,\right] \tag{1}$$

The flag q_i is +1 for minimisation objectives and -1 for maximisation objectives. The term $f_{i,t}^{avg}(k)$ is the average of $f_{i,t}(k)$ over a window [t-Δt, t+Δt]. Thus, the first term is the cumulative objective value over T years and the second term is the variation of the objective value over a period of 2Δt years around the current year t (Δt can be chosen as 2 and the adjustments in the start and the end of overall time period can be made accordingly). The parameters α and β adjust the importance of the two quantities—mean objective value and variation in objective value versus a running mean for the 50-year period. The term *p(k)* takes care of the satisfaction of adjacency constraints and is “distance-dependent” [18]. In our case, “distance” *D(k)* is defined as the numerical proportion of adjacency constraints violated:

$$D(k) = \frac{1}{P}\sum_{j=1}^{P}\frac{d_j(k)}{d_{j,max}} \tag{2}$$

For each of *P* polygons, the neighboring paddocks are checked for differences in their land use values. The term $d_j(k)$ indicates the number of paddocks (out of $d_{j,max}$ neighbouring paddocks) that are different in land use value. The term *p(k)* is set to zero if $D(k) \leq 0.6$ (meaning good adjacency arrangements); one, otherwise. The threshold of 0.6 is found to work well with a few trial and error runs. Thus, the presence of *p(k)* in the objective function should result in minimizing the number of violated adjacency constraints and the presence of $q_{i\ t}$ care of both minimisation and maximisation of objectives.

3.3 The epigenetic metaphor

Epigenetics describes heritable or partially heritable modifications in the phenotypic function or activity of a cell/organism that are not encoded in the DNA sequence. Key epigenetic processes that result in these modifications include DNA methylation and histone modification, which result in effects such as imprinting and gene silencing [14]. We focused on histone modification as our first tier of epigenetic emulation. Histone modification affects the structure of chromatin, which is a dynamic polymer including genomic DNA. Within the chromatin is a basic repeating structural unit called a nucleosome. Nucleosomes are made up of 146 base pairs of 2 super-helical turns of DNA wrapped around a core of 8 histone proteins. The histones are responsible for maintaining the structure and shape of the chromatin. Epigenetic modifications such as histone acetylation occur at the amino terminal tails of the histones that protrude from the nucleosomes [19]. Acetylation of histones is generally acknowledged to play a key role in the regulation of gene expression. Histone acetylation (influenced by intracellular environmental conditions such as cell cycle progression, DNA damage, DNA replication, etc.), is controlled by the balance and activity of 2 enzymes, Histone Acetyltransferase (HAT) and Histone Deacetylase (HDAC) [20]. During transcription, a gene must become physically accessible to the transcription process. Acetylation by HAT causes the uncoiling of DNA and an open chromatin structure, making a gene accessible (i.e., turned on). Conversely, deacetylation of histones by HDAC results in tight coiling of the DNA and a closed chromatin structure, making a gene inaccessible (i.e., turned off). This “on–off” phenomenon is known as position-effect variegation (PEV) [21].

For the land use management problem, we emulated the on-off histone modification on allelic gene regulation, which affected the 240 paddocks that each had 111 management options. During random selection at the start of the evolutionary search, management options for the 240 paddocks were randomly selected using a beta distribution that *biased* against options that maintained or changed land use to dairy. This was a deliberate attempt to minimise the environmental impact on nitrate leaching, which is high for this land use. It effectively improves the likelihood of evaluating land use plans that are responsive to the need to reduce nitrate leaching, while not eliminating other possibilities, as if fed back in an inhibitory fashion from the initial condition of the land uses. For the other 75 paddocks, a uniform distribution was used to randomly choose a land use change and/or management option.

The second tier of epigenetic gene expression that can be emulated (and we plan to execute next) was the post-transcriptional RNA editing, which happens before the genetic material is translated into proteins. The editing process is known to insert, delete or convert nucleotides [22]. We plan to emulate the latter for our land use management problem, where, following the protocols that emulated histone modification, the selected individual will be directly edited for violation of adjacency constraints. Large blocks of common land use will be identified from a population member (k) and the uncommon neighbouring paddocks of a block (say, j-th) will be converted to the common land use type using a probability proportion to ($1-d_j(k)/d_{j,max}$). In another attempt, the heredity-based epigenetic concept can be implemented by storing the information about the number of violated adjacency constraints on different regions on the non-dominated front and using the information at a later generation to create potentially useful offspring solutions. Hopefully, such an offspring will inherit from its parents an appropriate distribution of common land use types so as to have a better and suitable combination of objectives in that region on the Pareto-optimal front. When implemented, these sophisticated methods should speed up the evolutionary search method in converging close to the Pareto-optimal front.

The mutation operator of the evolutionary search algorithm can also be modified such that it would not violate the combined effect of the two-tier epigenetic emulation. Such an approach would provide an additional way for rapid appearance of locally optimised regions within the landscape, rather than relying on gradual accumulation of advantageous mutations over many generations, which would have meant long computation times and problematic convergence [1]. What we are therefore implying with our computational insight in the problem domain is that the evolutionary process, coupled with epigenetic changes and including a low rate of mutation, is better suited to adapting quickly to an environment in which certain alleles may be more favorable and spatially localised groups of loci may have advantageous interactions. In a way, the epigenetic changes are short-circuiting the evolutionary process with gene(s) accessibility control (on or off or with some intermediate bias). This is now verifiable experimentally [23], hence our confidence to test it out computationally in this complex combinatorial optimization problem.

4. Hyper-radial visualisation

The solution to our Evolutionary Multi-objective Optimisation (EMO) problem was a Hyperspace Pareto Frontier (HPF) with 100 solutions focused *near* the supplied reference points. With 14 dimensions it is not possible to visualise the trade-off space and single out a particular point that fits the purpose from the decision maker's perspective. To complicate the matter further, each trade-off point on the HPF represented 14 temporal outputs related to the 14 objectives, each extending over the 50-year planning period at 1-year intervals. It also represented the 11 time-series GIS vector layers showing the spatial land use change over the initial 10-year period and the final configuration of the following 40-year extended evaluation period.

Our inability as human beings to process multi-dimensional spaces [24] means that the quest to collapse hyperspaces into meaningful 2- or 3-D spaces is critical. For this land use problem, Hyper-Radial Visualisation (HRV) and 3-D trade space visualisation were simultaneously used to do "visual steering" towards a manageable number of trade-off points (which we called scenarios). Then a Multi-Criterion Decision-Making (MCDM) technique was applied to choose the compromise scenario based on preferences and values of the decision makers. We first describe the hyper-radial visualisation method and then discuss the MCDM method used in this pilot study.

4.1 Hyper radial calculations

HRV is a method for collapsing multi-dimensional plots to conventional 2-D plots [25], making it possible to single-out the preferred scenario among a set of trade-off solutions. The basic principle behind HRV is to normalise the objective functions, then divide them into two groups, each of which constitutes the basis of one of the axes of the 2-D plot. Converting the objectives into radial distances with x-y coordinates that are also normalised (taking values in the range [0,1]) makes it possible to plot the trade-off points on a 2-D plot. The trade-off point with the shortest radial distance from the reference point vector is then favored for that particular aggregation of objectives. We elaborate the calculations using our land use problem.

We had 100 non-dominated trade-off points, each defined by 14 objectives, as follows:

$$\left[F_1, F_2, F_3, \cdots, F_{14}\right]_j \quad and \quad j = [1,100].$$

Each objective function was normalised for minimization so as to create an artificial common point of reference, a null vector. Reference [25] used the utopia point for this purpose, but in our case we replaced the utopia point with the reference point vector that we used for the R-NSGA-II for consistency, and therefore our normalisation was as follows:

$$\tilde{F}_i^R = \frac{F_i - F_{i,lb}^R}{F_{i,ub}^R - F_{i,lb}^R}, \quad i = 1, \cdots, 14 \tag{3}$$

where,

ub = R-NSGA-II-based reference point upper bound, and

lb = R-NSGA-II-based reference point lower bound,

R = the reference point vector used in R-NSGA-II.

The objectives in equation (3) were then grouped into two sets,

Group 1: $\left[\tilde{\tilde{F}}_1^R, \tilde{\tilde{F}}_2^R, \tilde{\tilde{F}}_3^R, \cdots, \tilde{\tilde{F}}_s^R\right]$

Group 2: $\left[\tilde{\tilde{F}}_{s+1}^R, \tilde{\tilde{F}}_{s+2}^R, \tilde{\tilde{F}}_{s+3}^R, \cdots, \tilde{\tilde{F}}_{14}^R\right]$ (4)

and each group normalised as a radial distance providing the x-y coordinates of the 2-D HRV:

$$HRC1 = \sqrt{\frac{\sum_{i=1}^{s}\left(\tilde{\tilde{F}}_i^R\right)^2}{s}} \quad and \quad HRC2 = \sqrt{\frac{\sum_{i=s+1}^{14}\left(\tilde{\tilde{F}}_i^R\right)^2}{14-s}} \tag{5}$$

where,

HRC1 = hyper-radial calculation set for axis 1 of the 2-D plot, and

HRC2 = hyper-radial calculation set for axis 2 of the 2-D plot.

If the groups in (4) are uneven (i.e., $(14 - s) \neq s$), a 14-dimensional null vector can be added to avoid getting a skewed elliptical visualisation, maintaining the circular indifference curves as shown in Figure 2. Any non-dominated points that occur on the same indifference curve are equally important. Situations where the objective functions are unevenly distributed emphasize the bias that a decision maker might be looking for. A lesser number of objective functions on one axis will mean a greater bias towards those few than the rest of the objective functions on the other axis.

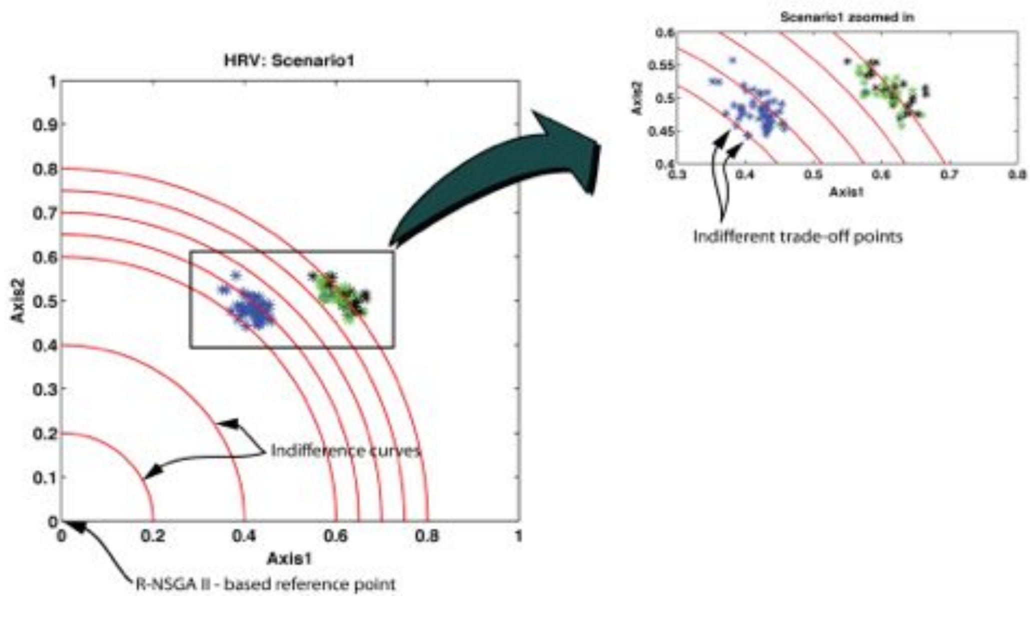

Figure 2. Hyper Radial Visualisation of the 100 non-dominated points, where the objective functions are evenly grouped for the two axes (or Scenario 1), showing the indifference curves, trade-off points (in different colours that represent the

uncertainty range, where blue is for Highly Desirable (meaning low uncertainty), green for Desirable, black for Tolerable and red for Undesirable (none were found)), and the R-NSGA II-based reference point at the origin.

4.2 Preferences and values

When preference weights are included in HRV, it enables the decision makers to incorporate their biases by assigning different weights to each objective function, resulting in changes in positions of the trade-off points and a different visual representation of the HPF in the HRV. These changes may mean a different selection of the most desirable solution under those prevailing preference weights. As for values, they are reflected in the "revealed preferences" [26] and our description here explains how we attempt to capture those values during the decision making process.

There are two prevalent approaches to allocating preferences in HRV, i.e., allocating weights for the different normalised objective functions such that these weights all sum to one, as in equations (6) and (7) [35]:

$$HRW1 = \sqrt{\frac{\sum_{i=1}^{s} W_i \times \left(\tilde{F}_i^R\right)^2}{s}} \quad and \quad HRW2 = \sqrt{\frac{\sum_{i=s+1}^{14} W_i \times \left(\tilde{F}_i^R\right)^2}{14-s}} \tag{6}$$

and

$$W_i \geq 0; \quad \sum_{i=1}^{n} W_i = 1 \tag{7}$$

where,

HRCW = hyper radial calculation with weighted preferences;

W_i= weight for the i-th objective;

$n = s$ for $HRW1$ and $14\text{-}s$ for $HRW2$

or, instead, defining preference ranges [25] without the explicit definition of weights. Much literature points to the difficulties of finding appropriate weights—for example, [25]—hence, of determining a preference for the ranges. However, in both the approaches it is *a priori* preferences that are captured and ultimately with similar concerns about difficulty of selecting appropriate weights.

Therefore, we have approached the problem differently, guided by our current understanding of what preferences are and how they relate to values. Our view agrees with current literature that preferences are unstable and that their acquisition exists on a continuum from familiar situations where they are retrieved, to unfamiliar situations where they are calculated based on relevant accessible information [27]. Values, in contrast, are stable, with cognitive consistency, are more internalized, and evoke strong "moral" emotions such as anger, contempt, disgust, guilt and shame [28]. Because of this moral aspect, which works at both the individual and cultural levels, we do agree with [28] that as preferences are calculated, they can in the process of "moralisation" be converted to values and also that the reverse, "amoralisation", can change values to preferences. Therefore, like behavioural decision theorists, we acknowledge that preferences can be continually developed/constructed and refined by taking into account context, which leads to changes or refinement of internalised values. Therefore, our approach attempts to bring the decision maker into determining a set of preferences that closely align with his/her internalised values through a familiarisation process that involves “visual steering”, or sometimes even challenges some of those internalised values.

The approach involves:

(a) Creation of a matrix of preference weights that will allow a graphical switch in the form of a slide bar at the bottom of the HRV that may be moved in real time, changing the positioning of the trade-off points;
(b) A second graphical output, with the 3-D trade space visualisation of the 14 objectives collapsed into the three composites: profitability, productivity and environmental impact, which highlights the changes in the ‘most desirable’ trade-off point as the slide bar is moved.

Figure 3 shows a combination of the above in two orientation angles in order to show all the four scenarios that were analysed using AHP [46]. This way, the decision maker is capable of choosing the most appropriate set of weights that closely resembles his/her values. Given that this is a complex multi-dimensional problem, it is most likely that the decision maker has never encountered such a problem before, and therefore preferences are most likely to be calculated/constructed, sensitive to context [28], rather than being retrieved from existing underlying preferences from familiar situations. Therefore, the 3-D trade space visualization is used to try to give the decision maker(s) a sense of direction, making it possible to choose contextual preferences that also may be closely aligned to internalised values. From Laird’s research [29], 75% of human attention is focused on sight and therefore the 3-D trade space visualisation provides the decision maker with qualitative information that may improve his/her preference construction. Once a selection has been made, an observation of the 11 time-series maps (current to year 10 at an interval of one year) showing land use change can be viewed to see whether the adjacent land uses are appropriately distributed. Appendix C shows a sequence of those maps for Scenario 3 (see Section 5.2 for the reason for choosing this particular scenario) as an example.

Drawing from the original concept of “design by shopping” [30]—an *a posteriori* approach to decision making, where trade space visualisation is used to construct preferences either during the optimisation process (which is actually computational steering and tremendously expensive) [31,32], or navigating the Pareto front [32,33,51]—we employ “visual steering”. A decision-maker’s preferences (using uncertainty-based HRV) are also aligned as closely as possible to his/her values through visual exploration made possible by the 3-D trade space visualisation. Therefore, we have named our approach “decision making by shopping”, because the approach takes the decision maker(s) into “preference calculation/construction” via a combination of uncertainty-based HRV and 3-D trade space visualisation, rather than requiring *a priori* preference weights.

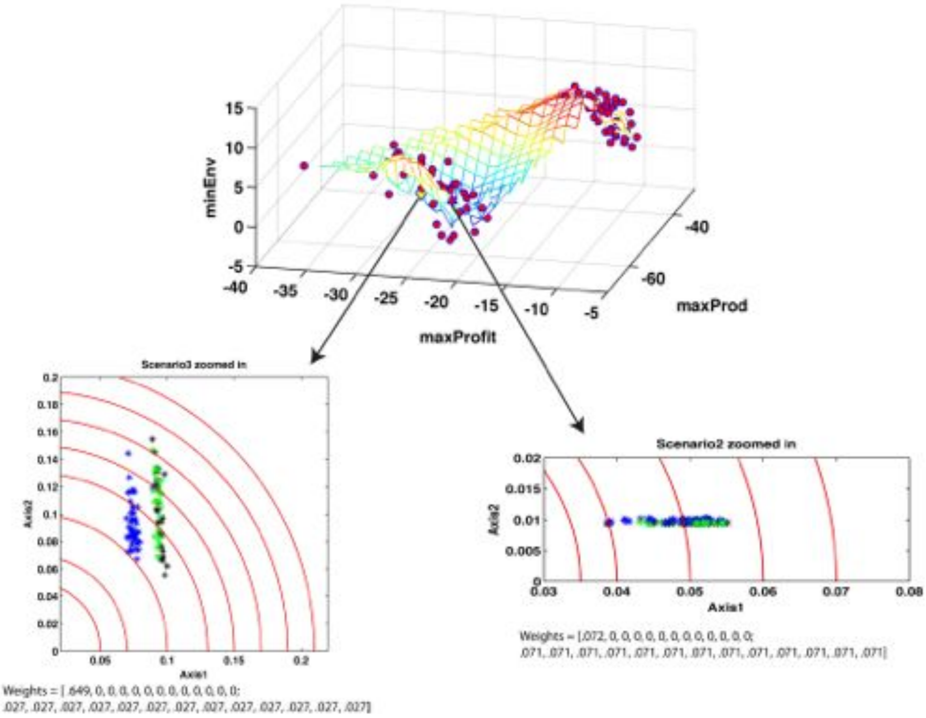

Fig. 3 a Scenarios 1, 2, and 4 can be seen in this figure.

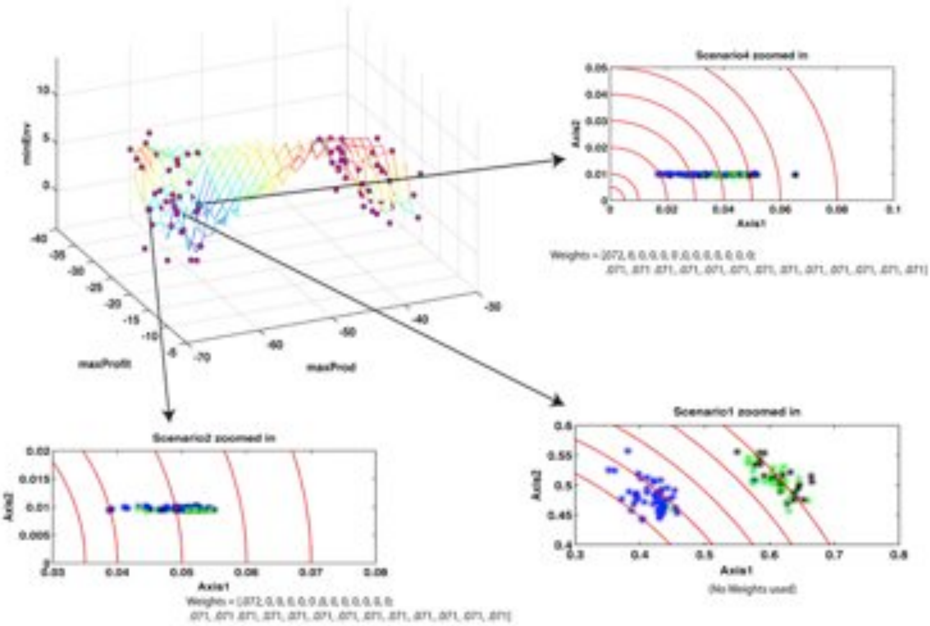

Fig. 3 b Scenarios 2 and 3 can be seen in this figure.

Figure 3a-b. 3-D trade space visualisation (in two orientations) with the four scenarios and their HRVs and weights (for Axis2 and Axis1, respectively), analysed using the AHP analysis.

This procedure is similar in concept to Pareto race [51], except that concept of visual steering is used on a non-linear Pareto front and therefore implemented in a non-parametric manner and by using hyper radial visualization (HRV) and virtual reality systems for understanding changes in time-varying land use paddocks.

4.3 Uncertainty ranges and visualisation

Given the uncertainties around the evaluation of the objectives, we incorporated them in the HRV in a way that enhanced visual steering, allowing a more informed and responsible decision-making process. This was achieved by using uncertainty ranges based on a concept borrowed from the Physical Programming approach for multi-objective optimisation [34]. A percent confidence/deviation value for each objective attribute from the trade-off set made it possible to compute the corresponding range bounds for each trade-off point:

$$F_{i,lb} = F_{ij} - \frac{F_{ij} \times \delta_i}{100} \quad and \quad F_{i,ub} = F_{ij} + \frac{F_{ij} \times \delta_i}{100}, \quad i = [1,14] \; and \; j = [1, 100] \tag{8}$$

where,

i = objective index;

j = trade-off point index; and

δ_i = allowable percent deviation value for each objective

= [3, 10, 10, 10, 3, 1, 1, 1, 2, 5, 5, 2, 5, 10] for water quantity, nitrate leaching, phosphorus loss, CO_2e, sediments, discounted costs, discounted income, discounted EBIT, milksolids, sawlog, pulpwood, beef, sheepmeat, and wool, respectively.

Each trade-off point was then converted to a distribution of points between the upper and lower bounds defined in (8) using an appropriate cumulative distribution function. The probability distribution percentage, PF_i, along the objective range could be computed between the lower and upper bounds of each objective. Given the incomplete knowledge of uncertainty for all the objective attributes, assumptions of equal probability were made based on our level of confidence in the simulation models and collated data used to construct the search space. This was in accordance with Bernoulli's Principle of Insufficient Reason or Equal Distribution of Ignorance [34, 35] that in the absence of any prior knowledge for an event, equal probability may be assumed. A probability threshold, Pr, is set and all trade-off points with a PF_i that falls under Pr are rated zero; otherwise, they are rated one. The sum of the ratings for each trade-off point was then categorised as follows: 11-14 was Highly Desirable, 9-10 Desirable, 7-8 Tolerable, and <7 Undesirable, with a matching colour coding scheme for the trade-off points as shown in Table 1 and demonstrated in Figure 2.

Pr was set at 0.4 following trial and error to find a suitable threshold that held a balance between having all trade-off points as either Highly Desirable or Undesirable. This value is also in agreement with other studies on HRV [35].

Trying to determine the uncertainty in the placement of the threshold will not be improved by using more and/or better quality data [36]. It is obviously subject to the inherent randomness in the behaviour of the system under study and therefore irreducible and falling into the general category of aleatory uncertainty [37].

Table 1. Uncertainty range for the obtained trade-off points

CATEGORY	**SUM OF PF_i VALUES**	**COLOUR CODE FOR TRADE-OFF POINTS**
Highly Desirable	11-14	blue
Desirable	9-10	green
Tolerable	7-8	black
Undesirable	<7	red

That means it is possible to have a final selection of a solution from the combined HRV and trade space visualisation that carries more uncertainty and it is up to the decision makers to either be bullish and go with it or search for another solution that will have less uncertainty. By allowing the decision maker to use imprecise probability definition, epistemic uncertainty due to lack of knowledge is accounted for.

5. Decision-making by shopping

Our approach to decision making by shopping has been motivated by a desire to "visual steer" via contextual preferences. [25] noted a complication with the *design by shopping* approach where a *designer* is guided to a solution via preference weights using a visual steering command, and the decision maker may not have knowledge of these preferences. We have reduced this barrier by using a combination of a 3-D trade space visualisation (that gives the decision maker a more visual and intuitive locational sense in his decision space) and an uncertainty-based HRV for doing oriented visual steering. The approach actually helps to construct preferences in unfamiliar situations, reaffirming the finding by behavioural decision theorists that preferences are contextual and therefore calculated during a decision making process [28].

5.1 Wide applicability of the 3-D trade space visualisation

Our approach of collapsing the 14 objectives into 3 composites—profitability, environmental impact and productivity—was suited to the land use problem. The breakdown was as follows:

(a) Profitability included the objectives: income, costs, and EBIT;
(b) Environmental impact included the objectives, nitrate leaching, phosphorus loss, sedimentation, water quantity and CO_2e; and
(c) Productivity included the objectives, beef, wool, sheepmeat, milksolids, sawlog, and pulpwood.

Worldwide, the awareness of finite resources has seen a shift in emphasis to pursuing the triple bottomline goal across many human endeavours. We can see how our approach may be generically applied to multi-objective optimisation problems for visualising HPFs in some specific industrial design areas by replacing the productivity composite with a performance one. For example, [38] noted that engineers in building space systems ought to now consider the fast changing political and economic context (where large defense contracts of the 1970s are now history), and the interdisciplinary expert opinion and diverse stakeholder preferences need to be taken into account for future designs.

5.2 Visual steering and trade space exploration

Four different uncertainty-biased HRV scenarios were used in each case to select the trade-off points closest to the R-NSGA II-based reference point through visual steering. These included:

(a) Scenario1 with an equal number of objectives on each axis of the HRV plot;
(b) Scenario2 with the income objective on one axis and the rest of the objectives on the other axis of the HRV plot;
(c) Scenario3 with the sedimentation objective on one axis and rest of the objectives on the other axis of the HRV plot; and
(d) Scenario4 with the nitrate leaching objective on one axis and the rest on the other axis of the HRV plot.

Reference [39] noted that decision makers wishing to emphasis a single objective function over all the others should group all other functions together on one axis with the objective of primary interest on the remaining axis. If that single objective function is weighted heavily it may ensure greater emphasis of that objective. For the purposes of this case study the preference weights were selected arbitrarily for the 4 scenarios. However, the 4 scenarios were chosen on the basis of the critical issues in the Rotorua District, and those are reducing nitrate leaching into the lakes and improving water quality. In the future, when all of our visualisation tools are integrated into a Virtual Reality Simulator that is being currently developed at the New Zealand Human Interface Technology Laboratory (NZ HITLab), Canterbury University, it will be possible to involve all the decision makers in selecting the scenarios and preference weights.

In the next step, the four trade-off points were ranked using a Multi-Criterion Decision Making (MCDM) method. At this point, however, all the relevant decision makers were involved. One of the important criteria for choosing a suitable MCDM method was the ability to define goals (i.e., desired end states) and befitting criteria linked to the scenarios in the decision making process. This is important because people tend to behave in a way that increases their likelihood to fulfill their goals [28]. Therefore, goals influence values and preferences. When goals change, so do the values and preferences [40].

5.3 Pairwise ranking and the multiplicative Analytic Hierarchy Process

There are many MCDM methods; some of the common ones include ELimination and Choice Expressing REality (ELECTRE) [41], the Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE) [42] and Analytic Hierarchy Process (AHP) [46]. Because of ranking irregularities [28] associated with ELECTRE and PROMETHEE [42] that are undesirable for a practical decision-making problem, we settled on the multiplicative AHP version

(M_{AHP}). M_{AHP} possesses the ranking reversal preservation property and effectively supports decision-making with regard to complex sustainability issues [43].

M_{AHP} is an effective Multi-Criterion Decision-Making (MCDM) method that ranks a number of alternatives by satisfying several conflicting criteria. It uses pairwise comparisons of all the decision elements obtained by breaking down the decision process into a hierarchy of sub-problems which are easier to evaluate —i.e., from the goal, to the criteria/objectives, to the alternatives (or scenarios in our case). Evaluation is achieved through eigenvectors and eigenvalues, which provide the priorities, and a means to check the consistency of the evaluations, thus reducing the bias in the decision-making. Summing up the product of the priorities for the alternatives with respect to the criteria and priorities for the criteria with respect to the goal, gives the ranking of the alternatives. If there are many decision makers, their priorities are aggregated as a geometric mean (hence multiplicative), rather than as an arithmetic mean (hence additive) that may lead to ranking irregularities [44]. This is because additive AHP tends to overweight the extreme alternatives and penalise the balanced alternatives [44,45]. It also suffers from ranking reversal.

Figure 4 shows the hierarchical levels for our problem; with the criteria broken into two levels (i.e., sub-criteria and objectives) to make the pairwise comparisons more intuitive, where under each criterion there are only objectives that are closely related.

6. Results and Discussion

6.1 Optimisation results

The 14-objective optimisation problem was formulated and solved using R-NSGA-II combined with the epigenetic metaphor on the MATLAB platform. The fitness function calculations were parallelised using the MATLAB Parallel Computing Toolbox on a dual 6-Core Intel CPU MacPro, and took 18 hours to run for 100 generations. In this pilot study, we have used α=0 and β=1 and demonstrate the working of both the multi-objective optimizer and the multi-criterion decision-making procedures proposed here. We plan to execute the complete procedure for other values of α and β including non-zero α values.

Figure 5 shows the value path (parallel coordinate) plot of the final generation of a R-NSGA-II run. The figure shows that a diverse set of solutions close to the supplied reference points (marked by green lines) is obtained. It is interesting to note that all 100 obtained trade-off solutions have an identical value for objectives 1 (water quantity), 3 (phosphorus loss), 6 (discounted cost) and 9 (milksolids), providing a common principle to these solutions. Such principles common to Pareto-optimal solutions were also observed in other engineering design problems and the task of discovering such principles using a multi-objective optimization method followed by an intelligent data analysis procedure is termed as *Innovization* [48]. Although an analysis of obtained trade-off solutions for an innovization study would be interesting, but in this paper we do not perform such a study, instead focus on an MCDM study.

The HPF had 100 solutions that in the 3-D trade space visualisation showed a disjointed HPF with two distinct clusters of trade-off points, as shown in Figure 3. The three axes (xyz) in the 3-D trade space were the composites: maximum productivity (i.e., beef, milksolids, sheepmeat, wool, sawlog, pulpwood, and water production), environmental impact (i.e., nitrate leaching, phosphorus loss, sedimentation and $C0_2e$) and maximum profit (discounted income, discounted costs, and EBIT).

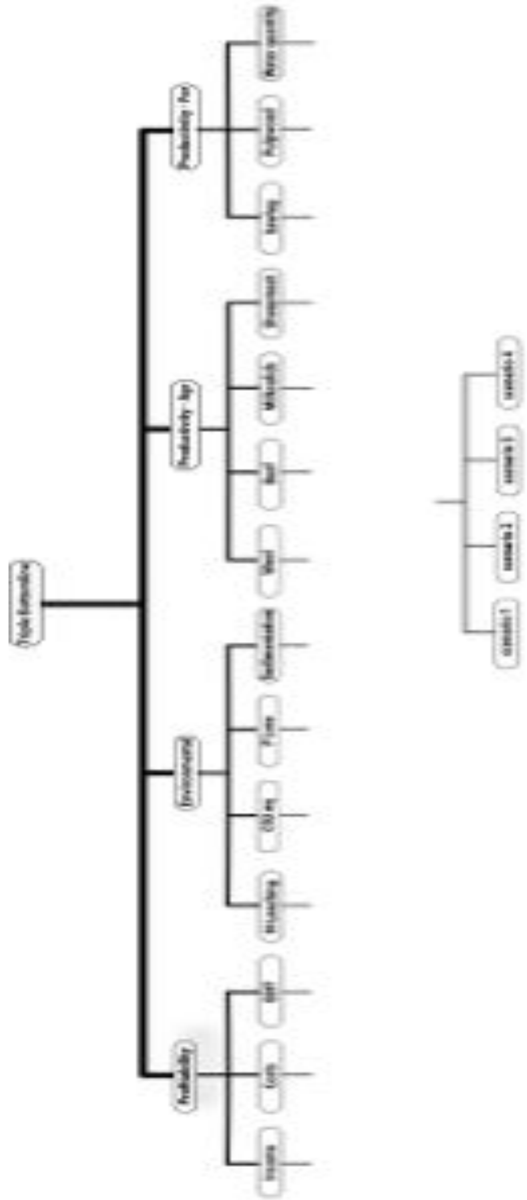

Figure 4. The hierarchy for the AHP analysis where for each objective, the four scenarios are compared pair-wise.

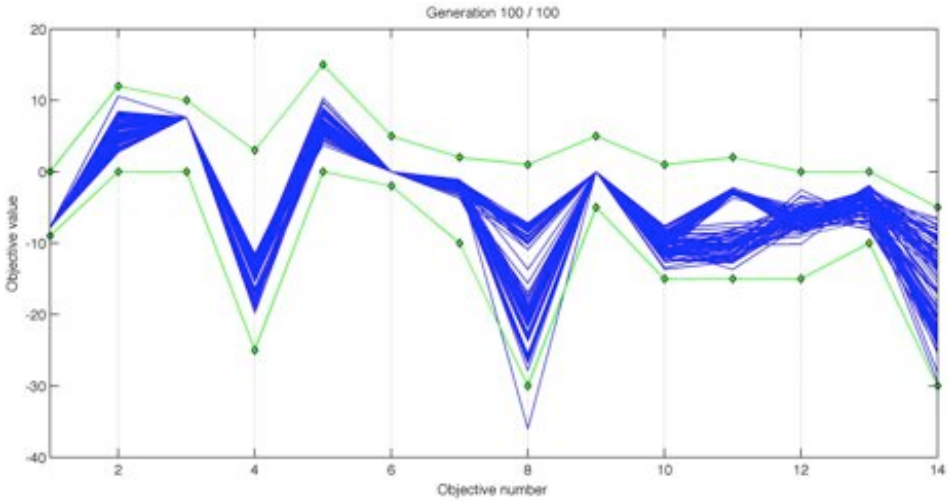

Figure 5. Value path (parallel coordinate) plots showing the range of 14 objective values obtained by R-NSGA-II. The green lines marked the range within which the reference points were supplied.

Through decision making by shopping, the 100 solutions were reduced to only 4, a manageable number that we could easily work with. All 4 scenarios that were chosen through decision-making by shopping were different and the user-group provided us with the preferences for MCDM analysis that at first seemed like conflicts reminiscent of interest groups with environmental positions that could never be compromised. Our view on that has now changed and we explain why later on in this section. All the trade-off points from the four scenarios were highly desirable in terms of uncertainty except for Scenario 2, where the trade-off point was tolerable as can be seen from a clearer zoomed image of its HRV in Figure 6.

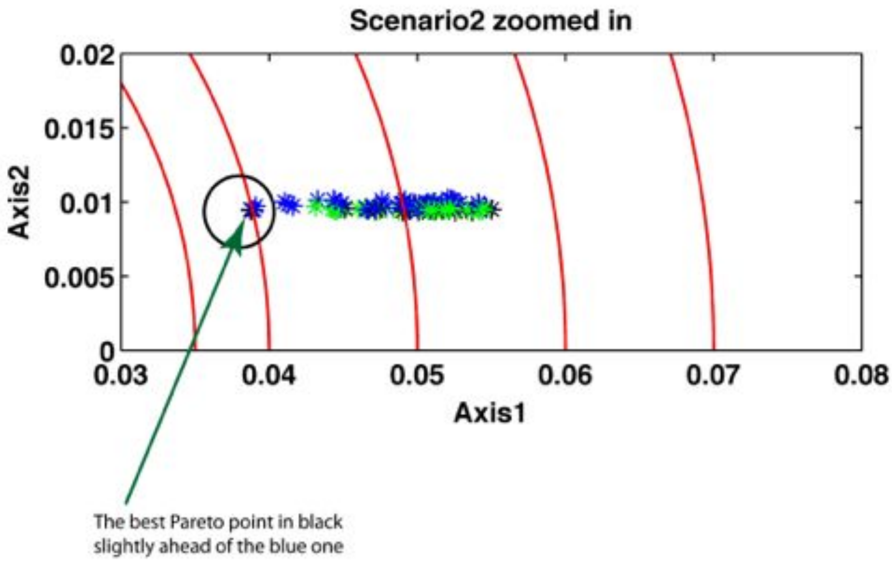

Figure 6: Zoomed in HRV image for Scenario 2.

6.2 Survey experience with the user-group

Given the sensitivity of environmental issues in the district, the participants' identities and their direct views and contribution will remain anonymous, and instead the experience is discussed in broader terms to avoid stereotyping any of the members.

To do the AHP analysis, we setup a user-group that consisted of:

(a) A NZ Maori landowner (given that the case study area is owned by a Maori Trust);
(b) A Senior Rotorua District Planner (given that the district council and the larger Bay of Plenty Regional Council (BOPRC) have a mandate to manage the commons without compromising economic growth);
(c) A Senior Waikato Regional Planner (because Waikato Region is a neighbouring regional council to BOPRC with similar environmental issues such as nitrate leaching); and
(d) Two Senior Forest Planners who participated as a team from a large private forestry company in the Rotorua District (since forestry is one of the main economic sectors in the region that is sensitive to land use changes).

The survey was carried out using 19 sheets per member that represented the 19 matrices of the AHP hierarchy shown in Figure 4. Saaty's linear 1-9 scale [46] was used for the preferences with intuitive images for criteria, objectives and scenarios, which helped to keep the members engaged and interested. We followed the Delphi approach by interviewing one member/team at a time to avoid group thinking. Each interview took about 90-120 minutes as the comparisons generated a lot of thinking and in some cases emotional expressions about issues. Goal preferences were quite revealing about biases of the members, although overwhelmingly, environmental issues were primary. Profitability was a major driver for one member although environmental issues remained paramount. It was quite evident that environmental issues are buried in the psyche of many in the district, testament to the effective messaging over the years by interest groups, Rotorua District Council and BOPRC.

A surprising observation was that there was no real appetite for sequestering carbon, given that NZ now has a carbon trading market. Note that the CO_2e in our models also included methane emissions from farm animals and represented a net value of carbon sequestered. Simple comparisons did not take time, but members seemed to deliberate on other comparisons and they tried to visualise in their minds possible cascading effects of their decisions: it was difficult to keep them focused on the pairwise comparison at hand.

Despite our concerns about possible hyperbolic discounting (i.e., ignoring future benefits), it was interesting to see common struggling to take future outcomes into account, particularly so when comparing the scenarios using the time-series plots in Appendix B. Only one member indicated a desire to take as much as logistics would allow and as early as possible for one particular product.

6.3 AHP results

The results from the AHP analysis are shown in the table below:

Table 2. AHP results for the 4 scenarios.

SCENARIOS	PRIORITIES	IDEALISED PRIORITIES
1	0.1316	0.6285
2	0.1757	0.8389
3	0.2094	1
4	0.1250	0.5971

Scenario 3 turned out to be the final choice and on close inspection tended to match all the disparate preferences of the members. Only after this analysis did it seem obvious from the Appendix B plots that Scenario 3 was indeed the best compromise. This was a learning moment for us as it dawned on us that only by aggregating the views of the members in the user group did it become apparent that Scenario 3 was the best. Scenario 2 was 84% as good as Scenario 3, and may be because it had the lowest milksolids and nitrate-leaching trends, but was penalised for high phosphorus loss. Another factor to consider here is also that Scenario 2 carried more uncertainty (i.e., was only in the tolerable range), and that was most likely because it had a comparatively healthy income due to having distinctly more production of wool and sheepmeat (mutton and lamb). The problem was that the NZ commodity prices for mutton and wool are volatile and on the decline. Without the uncertainty range, this problem would not have been flagged. Again here the strength of our approach was demonstrated—a very important characteristic of Scenario 2 that could have gone unnoticed if we had not taken model uncertainty into account.

Scenario 1 was 63% as good as Scenario 3, and this was the scenario that had no preference weights for the HRV and therefore would have seemed to be the one to pick, prior to the AHP analysis. Scenario 1 seemed like a very balanced option that would not really excel on any particular measure, but had almost everything well balanced. Nonetheless, the stakeholders agreed that a different compromise was superior for all. Finally, Scenario 4 was 59% as good as Scenario 3 and probably had the best-balanced forest harvesting ,which may have resulted in a better EBIT trend (i.e., more attenuated peaks and troughs), but suffered because of more sedimentation.

Given that for all the 4 scenarios, our model was heavily biased against dairy farming, the expectation was to see a complete replacement of it with other land uses. That did not happen, as it would have made it difficult to maximize the income and balance the EBIT. Instead, there was a reduction in the area allocated to dairy farming (as in Appendix C example) and for the remaining paddocks under dairying, a switch to low nitrogen management options, such as use of feed pads, low nitrogen feed supplements, nitrogen inhibitors and cut and carry systems were adopted. These results are consistent with the recent Rotorua District economy report [52] where dairy farming has contributed almost half (2.1%) of the total 5% growth for the region for 2012. Without dairy farming, the region would struggle, and our model makes suggestions on how to retain it but at the same time mitigating the environmental concerns.

All the matrices, 19 of them for each member in the user-group, were checked for inconsistencies, which may typically arise because of human error. For instance, to say that A is more important than B, and B is more important than C, where C has been declared more important than A, is being inconsistent. AHP relies on an effective inconsistency test that requires the computation of a Consistency Index (CI), which is then divided by the Random Index [46] to give a value of the inconsistency required. It should be less than 0.1, and details on the calculations can be found in MCDM literature such as [46]. In the consistency check process, a number of minor inconsistencies were found that were fixed without altering the intent of the members' preferences. Prior to these corrections, the results looked as in the following Table.

Table 3. AHP results for the 4 scenarios prior to correcting inconsistency errors.

SCENARIOS	PRIORITIES	IDEALISED PRIORITIES
1	0.1663	0.7387
2	0.1774	0.7882
3	0.2251	1
4	0.1345	0.5971

It is clear that the inconsistency corrections did not alter the ranking and only for Scenarios 1 and 2 did the idealised priorities change (without altering the ranking). It was a fairly time-consuming exercise to correct the inconsistencies, as care had to be taken to ensure that preferences of the members were not compromised. In the future, a computer program that will not only identify inconsistencies but also suggest changes that may fix the problems would be vital. Interestingly, such inconsistency information can also be fed back to the decision-makers in order for them to make a more informed decision-making task.

6.4 Joint construction of the view of the world

It is human nature to disagree, since human beings cognitively process information differently; therefore, objectivity becomes a key asset to achieving fairness. We used MCDM to achieve fairness, where different perceptions that resulted in different preferences seemed (in our minds) to lead to unresolved conflicts that would cause the members in the user-group to feel shortchanged and to revert to their original positions. What emerged, quite to the contrary, was that the different preferences of the members in the user-group only helped to clearly define a single view of the world (that each member could relate to), obtained through aggregation using an MCDM method.

Therefore, there is clearly merit for a landowner/policy maker/interest group to involve different stakeholders in the MCDM process, as it will help to define a complete view of the world. In other words, one is disadvantaged when "going it alone." This process could certainly have serious implications for how landowners, policy makers, and interest groups arrive at positions, recognising that accommodation of different views may only help to steer things to a more balanced and complete view.

Also, despite the complexity of the problem, we found out that the hierarchy concept behind AHP helped to break down the problem into simpler pairwise comparisons at different hierarchical levels, making it easier to understand. It is the simplification of such complex problems that made it interesting and engaging for parties involved. Our observation here may be similar to the Indian story about the 6 blind men who touched different parts of an elephant with their hands and had to describe the whole animal based on their evidence. It took someone who could see to aggregate the views of the 6 blind men to make them realise that a combination of their observations could more adequately describe an elephant.

In hindsight, we could have had more participants in the user-group to add views that could only have helped us to determine more refined preferences leading to a better choice for the farm, such as an environmentalist and a major tourist operator from the Rotorua District. We plan to include a much broader set of decision-makers in the near future.

7. Future research

The case study in this manuscript is about a single farm, albeit one divided into 315 separately-manageable paddocks. A regional problem would involve several farms, where the regional impact would be determined from the integration of the management intents of all the farms. Managing the interoperability of models of different farms and storage of information for regional analysis is no trivial task. It will be imperative to adopt a simulation interoperability framework, such as Urban OS™ developed by Living PlanIT [47] that will enable the synergy of distributed simulation models (where each model represents the operation of one part of the whole), thus enhancing the effectiveness of tracking "wicked" dynamics. The "plug and play" interoperability of these models/modules should also enable formation of a nerve centre for collection, retrieval and storage of large volumes of disparate and incommensurable data, utilised by the simulation models.

Although R-NSGA II was used successfully for the optimisation search, it is still a challenging task to choose *a priori* reference points for all the 14 objective functions, which will include the trade-off region of interest. We are still to experiment with different kinds of approximations that will help us focus on parts of the Pareto frontier that will most likely yield the desired solutions. However, [48] proposed a new NSGA-III approach for handling many objectives that is fundamentally different from other EMO approaches. This new approach can be tailored for this type of land use problem, augmenting it with reference points and epigenetic operators. But even without that, once fully developed, it will be applicable, in general, to other multi-objective optimisation problems, providing a new and viable direction for research and application in the evolutionary multi-objective optimisation (EMO) area. Like its predecessor (NSGA-II), we expect that NSGA-III will be popularly used, due to its ability to handle a large number of objectives better than its predecessor.

Our current epigenetic metaphor for the EMO was based on a predetermined, static epigenetic code, which worked well for this land use management problem. However, the biological epigenetic code in an individual is tissue- and cell-specific, and may change over time as a result of aging, disease or environmental stimuli (e.g. nutrition, life style, toxin exposure, etc) [16,49]. Our further research will seek to develop a dynamic epigenetic metaphor that will track the quality of the search (as the environmental stimulus) and continuously adapt in order to converge early to the Pareto frontier, in emulation of the biological epigenetic code. A breakthrough in such an endeavour could facilitate solving even larger evolutionary multi-objective optimisation problems.

Our VR simulator has no ability to deal with "psychological time" [24] because of the complex nature of time. General psychology identifies three aspects of psychological time, and our interest is on only one of them, which is time perspective as in conceptions about the past, present, and future [2]. It is bounded by cultural and/or religious beliefs and we tend to use the Newtonian concept [2] as the reference. Given that time is a construct that serves different practical, religious and scientific purposes, our future research will investigate a time construct to use in the VR simulator that will be less sensitive to hyperbolic discounting—i.e., ignoring of potential future costs/benefits. Preferences and values immune to hyperbolic discounting will be particularly important in addressing sustainability issues.

8. Conclusions

We have demonstrated a trans-disciplinary approach that includes the development of an innovative epigenetics-based multi-objective optimiser, uncertainty incorporation in the search space data, and decision-making by shopping on a multi-dimensional space through a combination of Hyper-Radial Visualisation and 3-D trade space visualisation, and Multi-Criteria Decision Making to select the final solution from the Hyperspace Pareto Frontier, based on the preferences and values of a diverse group of decision makers. Preferences and values of different decision makers are advantageous as a way of emphasizing different parts of the whole, and when aggregated help to identify the whole. Though our approach requires refinement, it provides a pioneering framework for "taming" complex societal issues or certain kinds of wicked problems. As is the nature of wicked problems, so too have we created other research questions that would need to be resolved to have a more refined taming.

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Appendix A: 14 objective functions ($obj_{i,t}(\mathbf{x})$) used in the study are presented in this appendix.

Milksolids model (NZ$/kg):

Milksolids(**x**) = 0.06729***x** + 0.5333*exp(sin(sin(0.3912***x**) - square(**x**) - 1.484/**x**)) + 0.172*plog(sin(2***x**)) + 2.014*cos(square(**x***exp(-**x**)) + sin(**x** + 2.556)) + 0.6326*sin(plog(**x** + 2.556)*(0.3912*square(**x**) + 0.5807/**x**)) + (0.172*sin(sin(**x** + 2.556)))/**x** - 131.4.

Real beef price model (NZ$/head):

Beef(**x**) = 21.69*plog(2*plog(sin(0.1746***x**))) – 115.4*plog(plog(sin(0.1731 ***x**)) + sin(0.4495***x**)) - 173.4*plog(plog(sin(0.1731***x**)) + sin(0.1697***x**)) - 75.08 *plog(sin(0.1731***x**) + 1183.0/**x**) + 1067.0.

Real mutton price model (NZ$/head):

Mutton(**x**) = 2.232***x** + 730.8*sin(cos(0.1605***x**)) +2.232.*cos(psqroot(-8.25) /cos(0.1207***x**)) - 280.6*tanh(cos(square(cos(0.1605***x**)))) - (1.357e6* cos(0.1605***x**))/**x** - 4212.0.

Real lamb price model (NZ$/head):

Lamb(**x**) = 11.62*tanh(cos(cos(**x**^2))) + 3.129*cos(exp(psqroot(psqroot(**x**)))) + 3.129*exp(psqroot(psqroot(**x**))) + 11.62*cos(**x**^2)*tanh(cos(**x**)*psqroot(**x**)) + 11.2*tanh(cos(cos(**x**^2)))*cos(**x**^2*tanh(cos(**x**))) - 17.33*cos(**x***tanh (cos(**x**)))*sin(sin(cos(**x**))) - 2453.0.

Real wool price model (NZ$/kg):

moving-max(**t**) = 1456*exp(-0.1091***t**) - 760.1 *exp(-1.114***t**);
moving-min(**t**) = 1096*exp(-0.08193***t**);
moving-med(**t**) = 1057*exp(-0.08144***t**);

Beta distribution with moving min, max, and median, used for Monte Carlo simulation, where their values are updated at 3-year intervals (i.e., **t** = 3).

All grades timber price (NZ$ /m³):

moving-max(**t**) = 66.69***t**^-1.916 + 88.43;
moving-min(**t**) = 43.39***t**^-1.629 + 86.45;
moving-med(**t**) = 63.88***t**^-2.273 + 88.06;

Beta or Triangular distribution with moving min, max, and median, used for Monte Carlo simulation, where their values are updated at 3-year intervals (i.e., **t** = 3).

Agricultural Interest rate:

moving-max(**t**) = 0.05452***t**^2 - 0.9419***t** + 11.29;
moving-min(**t**) = 0.03417***t**^2 - 0.7837***t** + 10.69;
moving-med(**t**) = 0.04548***t**^2 - 0.8831***t** + 10.78;

Beta or triangular distribution with moving max, min, and median, used for Monte Carlo simulation, where their values are updated at 3-year intervals (i.e. **t** = 3).

Forestry Interest rate:

max = 0.11;
min = 0.07;
med = 0.085;

Beta or Triangular distribution for Monte Carlo simulation.

Sheep and beef Cost factor:

moving-max(**t**) = 69.42 + 0.1547*cos(**t***1.46) - 2.52*sin(**t***1.46);
moving-min(**t**) = 0.075***t**^2 - 2.245***t** + 73.38;
moving-med(**t**) = 1.405e5*exp(-5.295***t**) + 66.63*exp(-0.002763***t**);

Beta distribution with moving min, max, and median, used for Monte Carlo simulation, where their values are updated at 3-year intervals (i.e. **t** = 3).

Dairy Cost factor:

Dcostfactor(**x**) = 0.04662***x** + 0.02106*plog((cos(**x**) + 0.9934)*(sin(**x**) + 0.9934)) + 0.02556*cos(cos(2***x**)*(**x** - 5.166)) + 0.4849*plog((3***x** - 5.166)*(sin(**x**) - 5.166)) - 97.76,

where,

x = time vector at yearly interval;

plog = MATLAB function to calculate the element by element protected natural log of a vector; and

psqroot = MATLAB function to get the element by element protected square root of a vector.

Commodity prices and interest rates predictive models estimated using GPTIPS Genetic Programming or predictive statistical models are presented next.

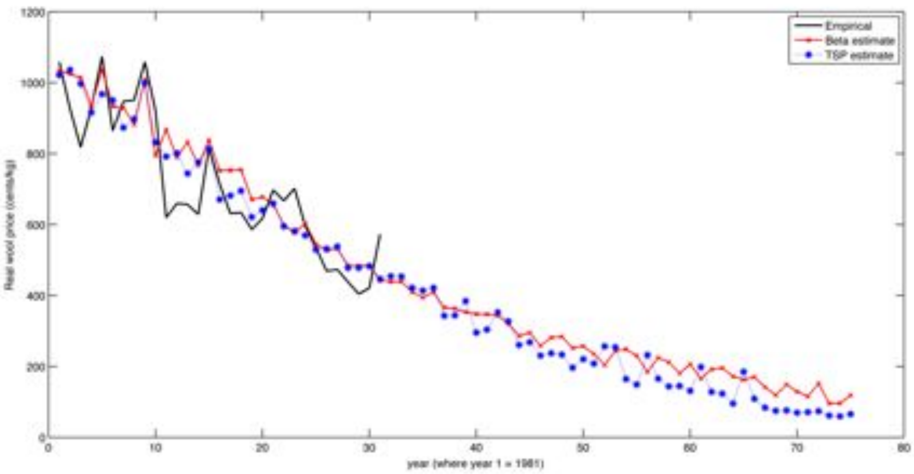


Figure A1: Wool price model. Notice how both Beta and triangular distribution are able to learn from past years and are able to predict wool price for the future.

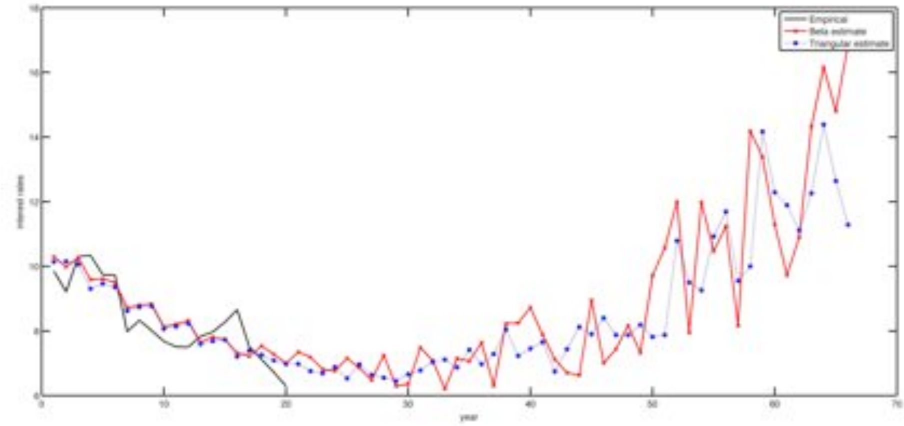


Figure A2: Agricultural interest rate (with empirical data from ANZ bank, New Zealand). Although the positive trend beyond year 30 may come as a surprise, this happens due to the inclusion of a trend analysis over a three-year time window.

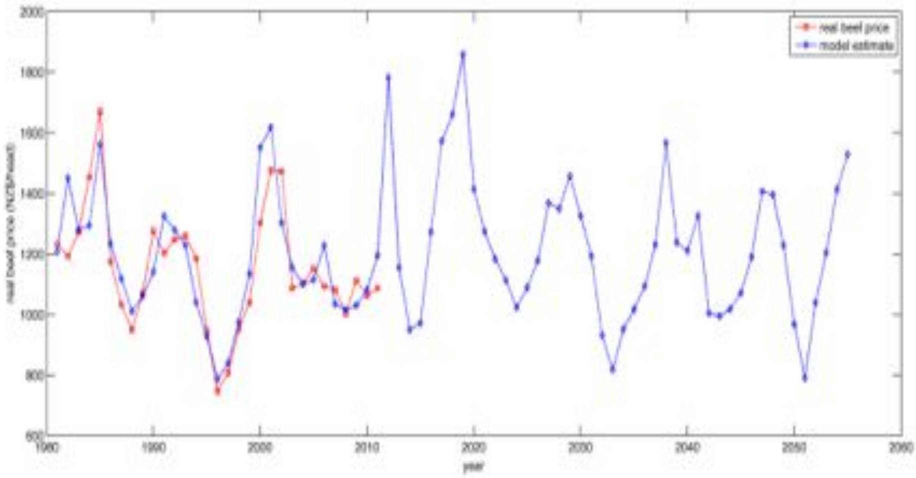
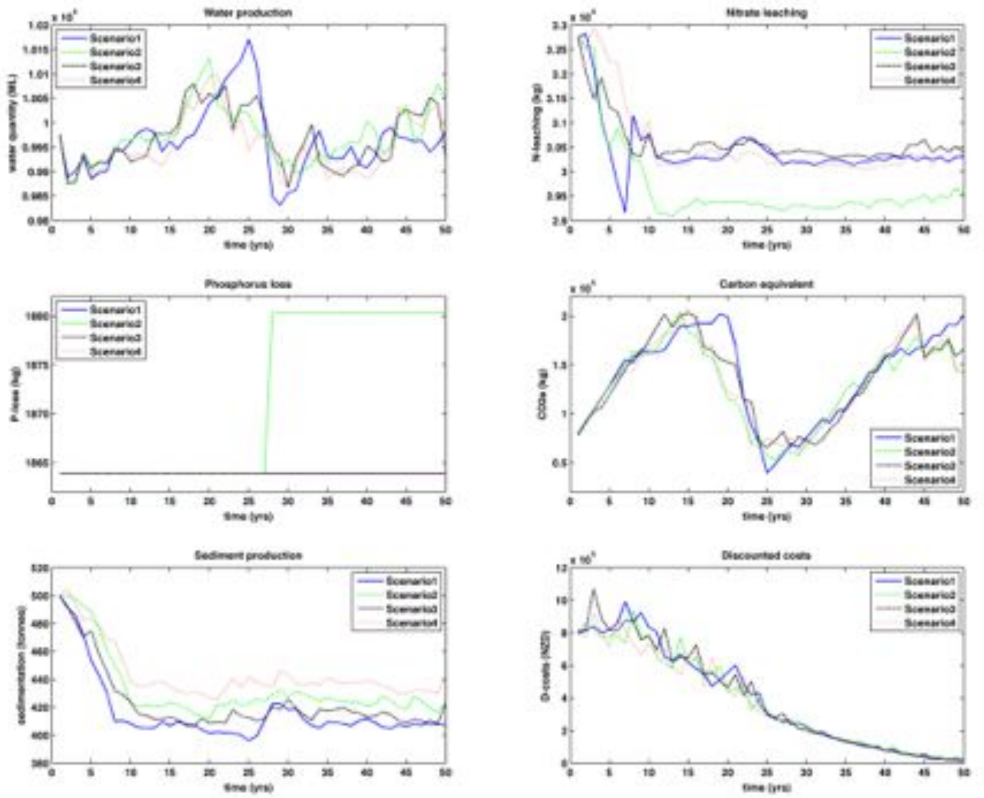
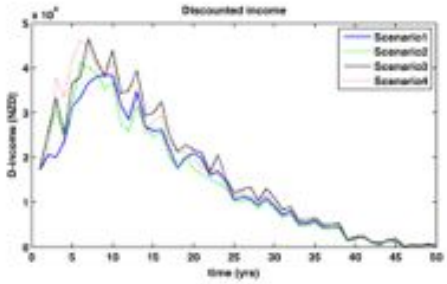


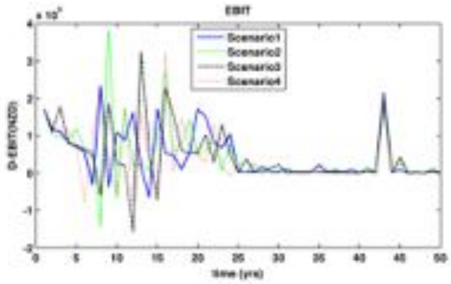
Figure A3: Real beef price model. Due to large fluctuations present in the beef prices at the empirical data, the prediction beyond year 2010 also seems to have a large fluctuation.

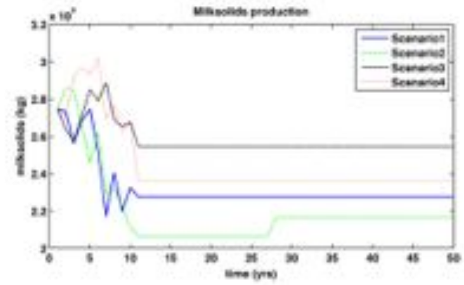
Appendix B: The 4 scenarios with their outputs compared for the AHP process. It is not intuitively clear which of the four scenarios would be preferred. A subsequent AHP analysis helps us determine the preferential advantage of Scenario3.

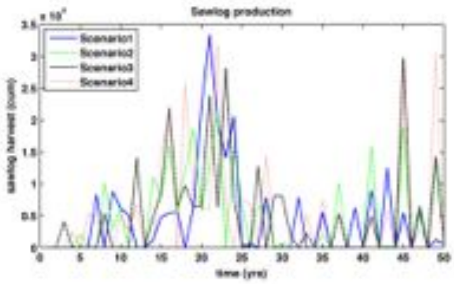


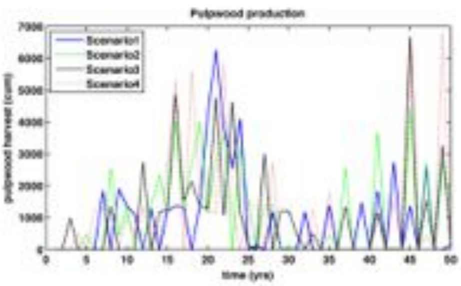
Appendix B (cont.)

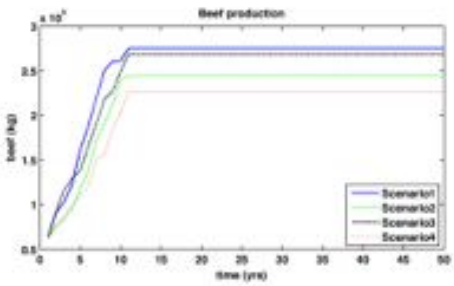


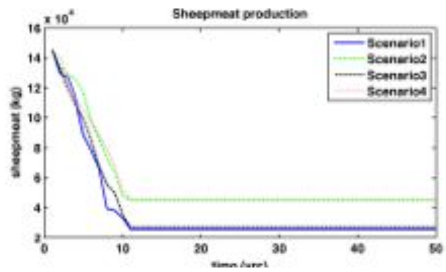


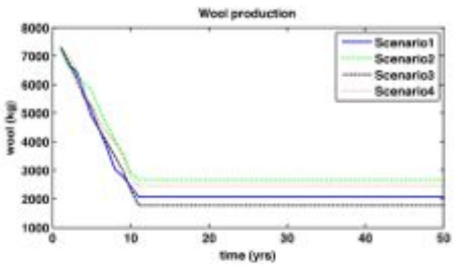




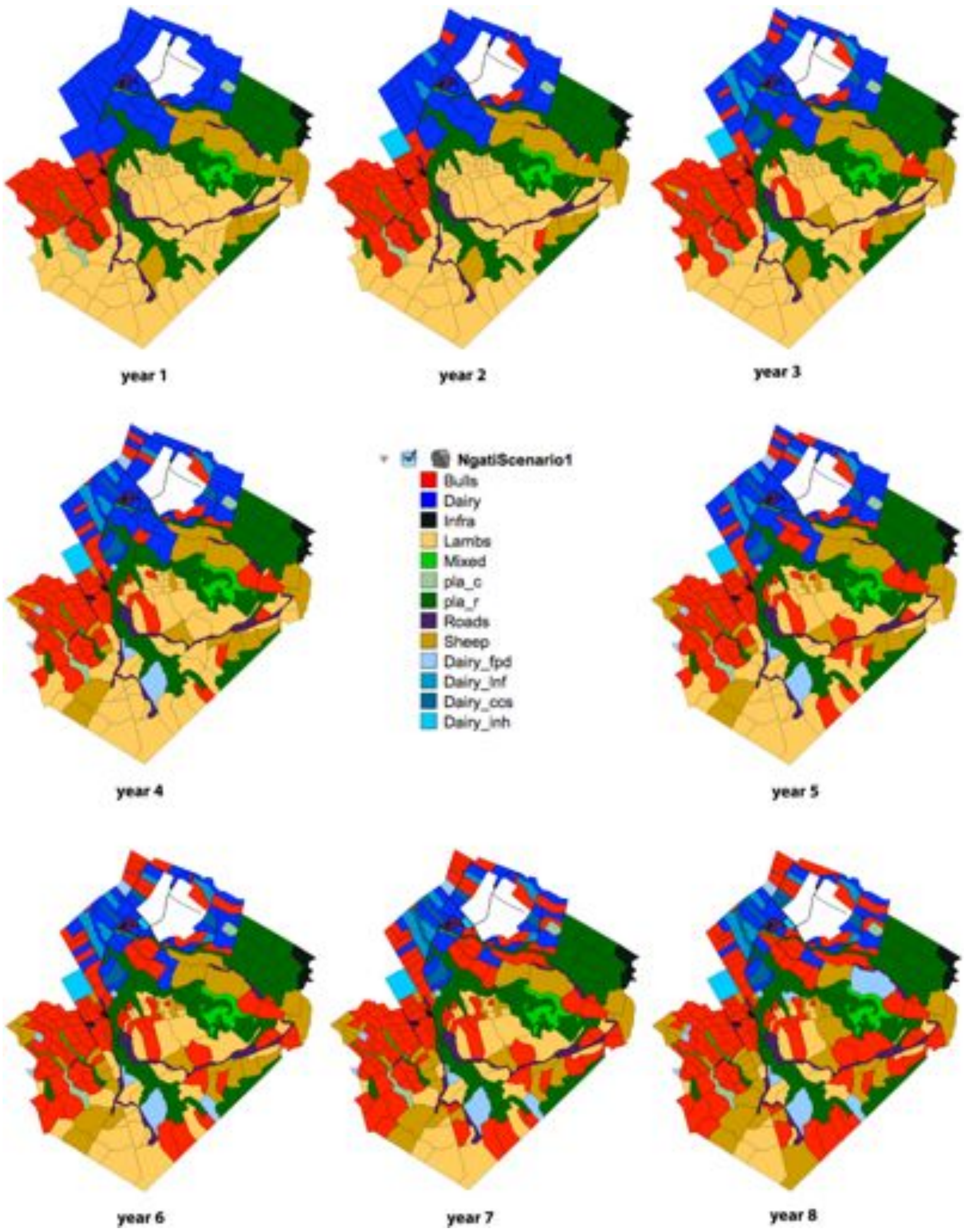




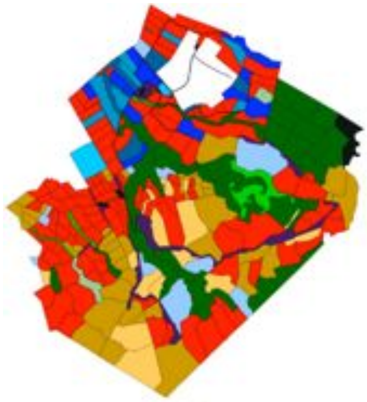




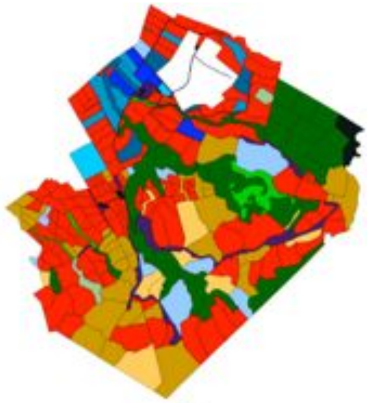
Appendix C: Time-series maps of the property of the case study for Scenario 3 land use changes from year 1 to year 10 and year 50.



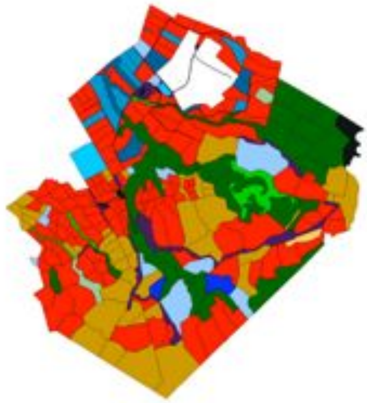
Appendix C (continued)



year 9



year 10



year 50

It is clear that 50% sharemilking from year 1 (i.e. Dairy from the legend) is almost completely eradicted because of the high nitrate leaching. The remaining dairy operation has been converted to better management options that have a much smaller environmental footprint, i.e., the following:

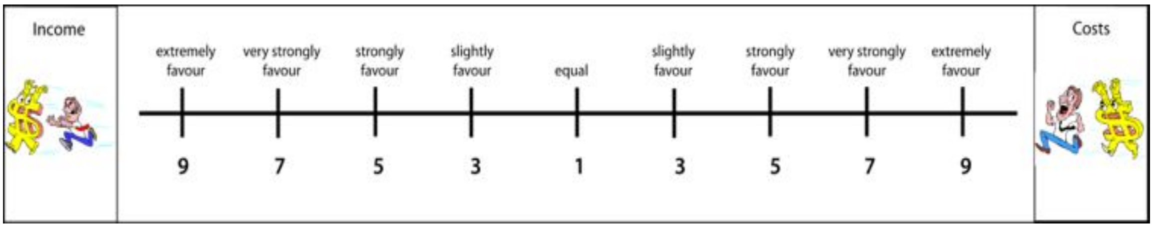
- The Feed Pad option where the animals are off farm grazing in winter (i.e. Dairy_fpd),
- The N Inhibitor added to fertilizer to minimise leaching (i.e. Dairy_inh),
- Use of low nitrogen feed supplements such as maize silage (i.e. Dairy_lnf), and
- The cut and carry system where the animals are kept in a shed for 10 months of the year.

All these changes have costs associated with them and our model has taken that into consideration. The most likely reason why dairy farming has been kept is because the commodity price curve keeps rising and therefore, our model tries to keep that land use for as long as possible but also switching to environmentally friendly options.

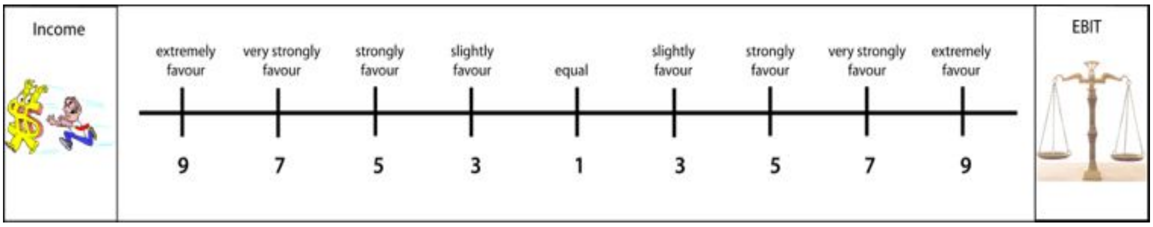
Appendix D: A sample of the survey sheet for the AHP Profitability Criterion preferences.

Profitability Criterion Preferences **Decision-maker : _________**

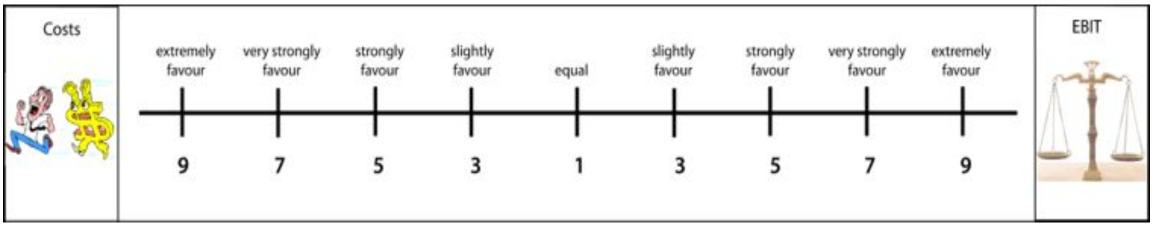
1.2



1.3



2.3



L = actual judgment value **R** = reciprocal value