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## Author

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LETTER

# Navigating Complex Decisions in Restoration Investment

Luke P. Shoo[1], Carla P. Catterall[2], Sam Nicol[3], Rochelle Christian[4], Jonathan Rhodes[5], Penny Atkinson[4], Don Butler[6], Roger Zhu[7], & Kerrie A. Wilson[1]

[1] School of Biological Sciences, The University of Queensland, St Lucia, QLD 4072, Australia
[2] Environmental Futures Research Institute, School of Environment, Griffith University, Nathan, QLD 4111, Australia
[3] Land and Water, Ecosciences Precinct, CSIRO, Dutton Park, QLD 4102, Australia
[4] Department of the Environment, Australian Government, Canberra, Australia
[5] School of Geography, Planning and Environmental Management, The University of Queensland, Brisbane, QLD, Australia
[6] Department of Science, Information Technology, Innovation and the Arts, Queensland Herbarium, Toowong, QLD 4066, Australia
[7] School of Business, The University of Queensland, Brisbane, QLD, Australia

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**Correspondence**
L.P. Shoo, School of Biological Sciences, The University of Queensland, St Lucia, QLD 4072, Australia. E-mail: l.shoo@uq.edu.au

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## Abstract

Ecosystem restoration requires choosing among potential interventions which differ in cost, and the time required to achieve outcomes of varying quality. Managers have different preferences for timeframes, certainty, and quality of outcomes, which can influence the choice of investment strategy. Here we develop a probabilistic approach to quantify expected restoration outcomes from alternative investment strategies, given operational constraints or alternative preferences. We apply the approach to a tropical forest restoration case study in which managers seek to allocate future resources between active planting and self-organized regrowth. We find that the best strategy depends on the desired forest attributes and the time required for outcomes to be achieved. We quantify the trade-off for three key forest attributes between restoring large areas of vegetation to low quality and restoring smaller areas to a higher quality. Explicit consideration of preferences and trade-offs will enhance the likelihood that projects deliver desired outcomes.

## Introduction

Direct payments schemes are an important tool used by natural resource managers to achieve conservation of biodiversity (Ferraro & Kiss 2002) and promote activities that protect or recover ecosystem services (Wunder 2013). A challenge of direct payment schemes, however, is how to allocate scarce financial resources among competing projects to maximize return on investment. Environmental restoration schemes are particularly challenging in this regard. First, the desired outcomes can differ among stakeholders (e.g., carbon storage versus habitat for wildlife) and their measurement is often unclear (Wortley *et al.* 2013). Second, restoration of degraded systems involves uncertainty and time lags over several decades (Holl & Aide 2011). Third, restoration involves a range of potential actions, each with their own costs, time frame and likelihood of success (Wilson *et al.* 2011).

On face value, intensive interventions that deliver more immediate outcomes might be favored over less-intensive projects. However, strategic decisions about whether to invest in projects are also influenced by cost, land availability, and preferences for timeframe, certainty, and the quality of the environmental outcome (Holl & Aide 2011). Preferences are an important but rarely evaluated component of restoration decision making (Stanturf *et al.* 2014). There is limited guidance on how (or to what extent) the best strategy for direct investment in restoration might be influenced by stakeholder preferences. This is despite the fact that restoration decisions involve complex value systems and high uncertainty and managers are increasingly accountable for expenditure of public funds (Hobbs 2009).

Here we develop a new approach to quantitative decision support for planning future interventions which maximize the return on investments in ecosystem restoration. We ask four questions: to what extent is the "best" investment strategy determined by (1) how outcomes are measured; (2) the expected quality of the outcome; (3) how soon benefits are required; and (4) preference for certain outcomes? The approach is illustrated using a case study of reforestation within an agricultural region of tropical northern Australia, where substantial investments have been made to recover native rainforest. In this study region, the nature, outcomes, and costs of different restoration actions have been researched and documented (Catterall *et al.* 2008; Shoo *et al.* 2016). We assume that a fixed budget is allocated between two alternative restoration actions: intensive biodiversity planting and self-organized regrowth. Each action is applied exclusively to a specified number of land parcels within a funded project area. Our approach establishes a conceptual basis for resolving more complex situations (e.g., more than two restoration actions, additional preferences) and informing resource allocation decisions across different ecosystems, regional management contexts, and types of action.

## Methods

### Case study system

The case study region covers 920 km$^2$ in the Atherton uplands (17°10′–17°35′S, 145°30′–145°45′E) of the Australian Wet Tropics. Much of the indigenous rainforest on this upland plateau was cleared for agriculture early in the twentieth century, leaving small remnant patches amidst pasture and cropland (more extensive forest tracts being restricted to adjacent slopes). From the late 1980s to the early 2000s several major initiatives publically funded restoration (Catterall *et al.* 2004, 2008). Individual projects involved tree planting of diverse species at high density, with the aim of reinstating local vegetation communities (Catterall & Harrison 2006; Freebody 2007). At the same time, change in land use has allowed self-organized regrowth (unassisted succession) to occur in some areas (Figure 1). The developmental trajectories of this regrowth and the intensive "biodiversity plantings" represent extremes on a spectrum of passive to active restoration interventions and were quantified for a range of ecosystem attributes by Shoo *et al.* (2016).

### Outline of approach

We assume that the overall goal is to restore forest for a strategic purpose (e.g., biodiversity or carbon recovery) and that a decisionmaker must decide how to invest in restoration actions to maximize desired outcomes. Our aim is to characterize how allocation of a limited budget to different restoration actions (hereafter "alternative investment strategies") affects both the total area managed and the aggregate area restored to predefined minimum levels of vegetation quality, given different timeframes and levels of certainty that outcomes will be delivered (see Figure 2). We tackle this problem in three steps.

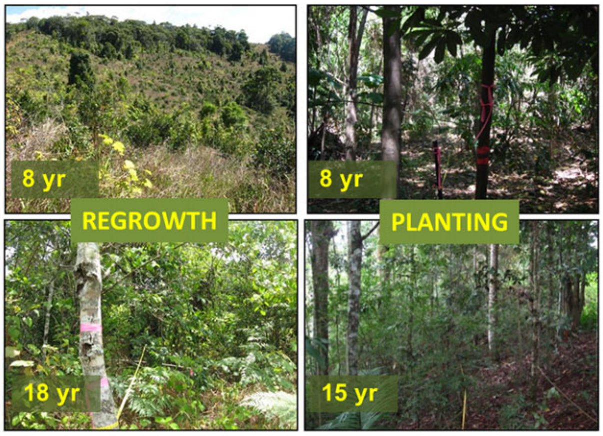


**Figure 1** Illustrative examples of reforestation pathways in the Australian Wet Tropics (Photographs by Kylie Freebody).

### Step 1: Probability of exceeding minimum levels of vegetation quality

Developmental trajectories for two restoration actions (self-organized regrowth and biodiversity planting) were quantified using age chronosequences and benchmarked against old growth reference forest (Shoo *et al.* 2016). Relationships between site age and development were then characterized against three performance measures. Each performance measure was a desirable vegetation attribute of native forest: (1) canopy cover as an indicator of ecosystem function, (2) wood volume as an indicator of carbon storage, and (3) floristic composition as an indicator of biodiversity (calculated as the multivariate similarity to reference forest of native tree and shrub species >1.0 m tall). We assumed that land available for restoration was initially in an unvegetated state (i.e., pasture with negligible remnant trees or shrubs) and that outcomes for each land parcel were independent of each other.

The probability of exceeding a minimum level of vegetation quality depends on the performance measure (vegetation attribute), restoration action, timeframe, and minimum desired quality of the outcome. We considered three vegetation attributes (see above), two restoration actions (regrowth or planting), and two timeframes (1–10 or 15–27 years). Selection of timeframes was governed by available temporal replication in the chronosequence

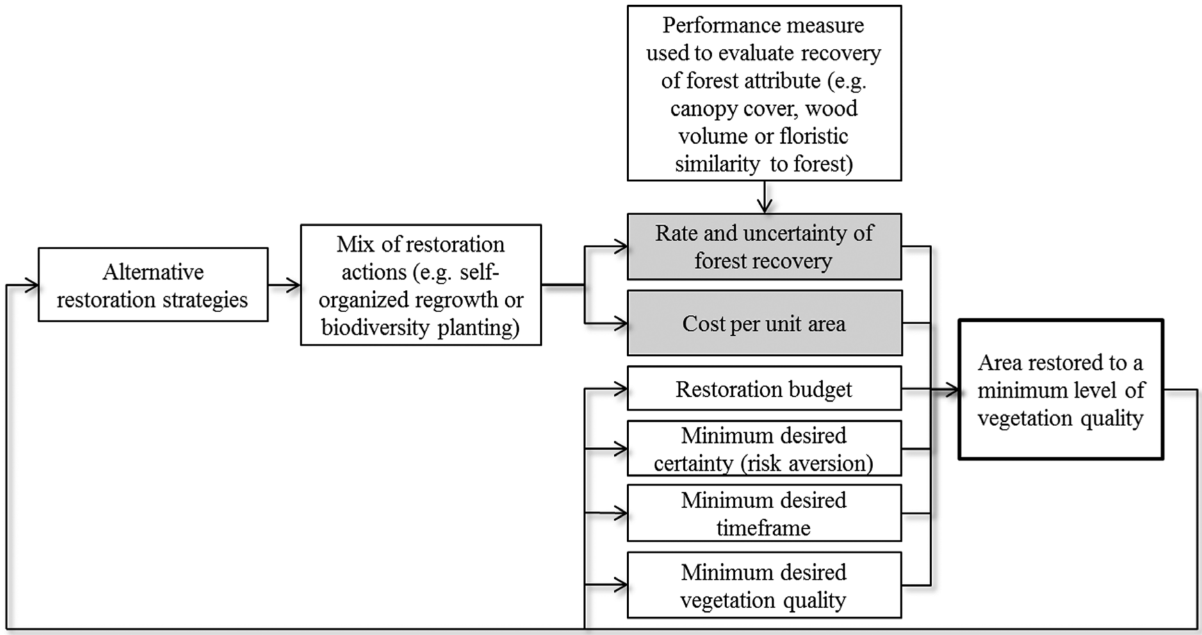


**Figure 2** Conceptual overview of approach to support restoration decision making. Feedback arrows indicate that an iterative process may be followed to select a suitable investment strategy. Estimates of expected outcomes might prompt decisionmakers to explore an alternative restoration strategy, reappraise their preferences for important attributes of the outcome (e.g., timeframe, vegetation quality, certainty) or reconsider budget commitments.

data (Regrowth sites: $N = 6$ for both <10 years and 15–27 years old; planting sites: $N = 8$ for both <10 years and 15–27 years old). We attempted to control for land use history when establishing reforested sites but recognize that other elements of context (e.g., amount of surrounding forest) might be a source of variation in our vegetation recovery data (Crouzeilles & Curran 2016). Although not explicitly considered here, where such data exists, it would also be possible to factor these elements into the framework to reduce uncertainty in expected outcomes. Quality thresholds for restored vegetation (regrowth or planting) were defined as reaching at least 25%, 50%, or 75% of the mean attribute value of a common set of reference forest sites ($N = 8$). The probability of exceeding each vegetation quality threshold was then derived for each combination of vegetation attribute, restoration action, and timeframe, by fitting appropriate probability distributions to the chronosequence data and estimating the area under the distribution above the quality threshold (see Figure 3) using the "MASS" package in R (Venables & Ripley 2002). We fit $\beta$ distributions to continuous data where attributes had fixed lower and upper bounds (percentage canopy cover and proportional floristic similarity) and lognormal distributions to data with a fixed lower bound (positive values for wood volume).

## Step 2: Alternative investment strategies

Our unit of investigation is an individually funded restoration project, each one hectare in area. The total project area then is function of the budget and the proportion of the budget allocated to either regrowth and planting projects that differ in cost per hectare. The baseline initial restoration cost was AUS$10K for each one hectare project. This investment covers the initial actions needed to reallocate land to conservation purposes (e.g., remove grazing livestock and install fences). Vegetation recovery could then be further accelerated by planting, however this imposes an extra cost of AUS$40K per hectare (Catterall & Harrison 2006; Hunt 2008). This additional investment comprises the funds needed to implement the "biodiversity planting" method (see Shoo *et al.* 2016). Thus, the total unit cost of regrowth and planting projects were $10K and $50K respectively, meaning that a manager with a fixed budget in planting-only projects would restore one-fifth of the area achievable in regrowth-only projects. We used a fixed budget of AUS$500K to explore three alternative investment strategies: 100% planting projects (allP), 50% each of planting and regrowth projects (R&P), and 100% regrowth projects (allR); the resultant total area under management varied from 10 to 50 ha (Table 1).

 

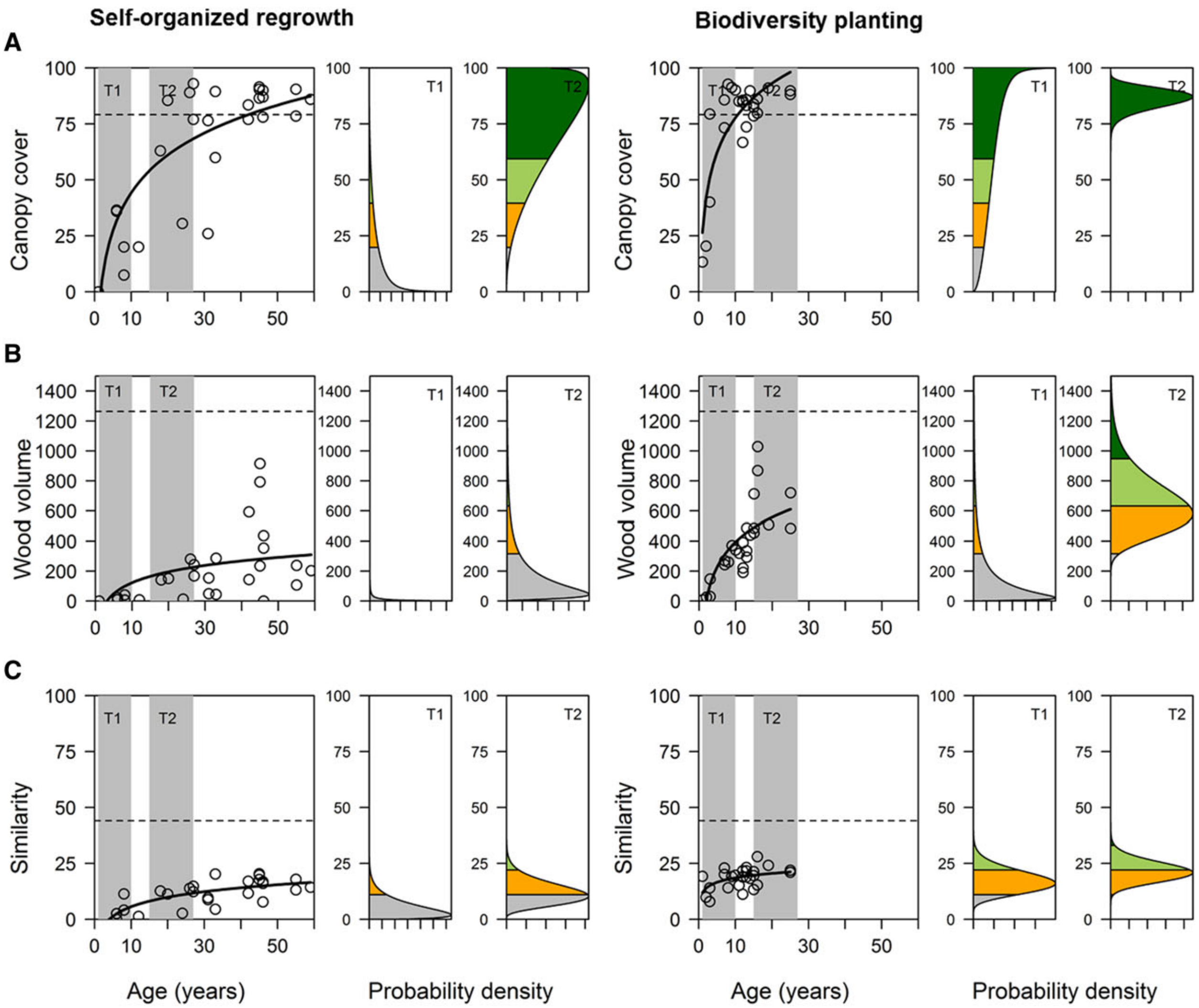


**Figure 3** Temporal development of forest attributes (canopy cover, wood volume, and floristic composition) following self-organized regrowth (left panels) or biodiversity planting (right panels) in the Australian Wet Tropics. Values for attributes are benchmarked against mean reference forest values (broken lines), which were 79.15 % for canopy cover, 1263.2 $m^3$/ha for wood volume and 0.44 for floristic composition. Solid lines show fitted values of the modeled relationship between vegetation attribute and log-transformed age. Also shown are probability distributions of outcomes fitted to data (see methods) for two time periods: T1 (range 1–10 years) and T2 (range 15–27 years). Self-organized regrowth sites: $N = 6$ for both T1 and T2; Biodiversity planting sites: $N = 8$ for both T1 and T2. The area under each probability distribution that correspond to different levels of minimum vegetation quality are highlighted as follows: <25% (grey), 25– 50% (orange), 50–75% (light green), and >75% (dark green) of mean reference forest values.

## Step 3: Expected outcomes from alternative investment strategies

Given a particular investment strategy, the probability that a certain number of projects would reach or exceed a vegetation quality threshold is given by the cumulative Poisson binomial distribution (i.e., the distribution of the sum of independent and non-identically distributed success/failure experiments; see Hong [2013] for an analytical expression of the cumulative distribution function). For a given timeframe and vegetation quality threshold, the probability of success varied according to the restoration action applied to each project. In investment strategies where the entire budget was allocated to projects that adopted the same restoration action, success probabilities were equal and the Poisson binomial distribution was a standard binomial distribution. In the "50–50" planting-regrowth strategy, the success probabilities could take one of two values for each performance measure, depending on the action applied to the target project. We used the "dpoibin" function of the "poibin" package in

**Table 1** Potential alternative investment strategies – allocation of budget among restoration actions assuming a fixed budget of $500K and base rate costs for self-organized regrowth and biodiversity planting of AUS$10K and AUS$50K, respectively

| Alternative investment strategies | Percent budget allocated to planting | Percent budget allocated to regrowth | Area managed as regrowth (ha) | Area managed as planting (ha) | Total area managed (ha) |
|---|---|---|---|---|---|
| All regrowth (allR) | 0 | 100 | 50 | 0 | 50 |
| Regrowth and planting (R&P) | 50 | 50 | 25 | 5 | 30 |
| All planting (allP) | 100 | 0 | 0 | 10 | 10 |

R (Hong 2014) to calculate the cumulative Poisson binomial distribution with success probabilities weighted by the number of projects assigned to regrowth or planting.

The expected outcomes from each alternative investment strategy were then derived from the Poisson binomial distribution using the "qpoibin" function of the "poibin" package in R (Hong 2014) given two scenarios of preferences for certainty. "Neutral" and "averse" scenarios were defined as a 50% or 90% chance of achieving prespecified outcomes, respectively (i.e., 0.5 and 0.1 quantiles of the Poisson binomial distribution). The approach was repeated for the three alternative performance measures.

## Results

The probability of exceeding minimum levels of vegetation quality increased with time and in response to more intensive restoration intervention (planting vs. regrowth; Figure 3 and Table 2). However, probabilities also differed among the three forest attributes used to measure restoration outcomes. For example, there is a moderate ($\geq$0.5) to high ($\geq$0.9) probability that canopy cover can be reinstated to near forest reference values within 15–27 years following either regrowth or planting, unlike wood volume and floristic composition which developed slower and would rarely reach reference values within 15–27 years. For these latter attributes, few land parcels are likely (i.e., high probability) to be reinstated to a minimum vegetation quality over a comparable timeframe and, even then, only in cases where there is investment in planting.

For canopy cover, the area over which vegetation quality exceeded the 25% threshold was indifferent to the relative allocation of budget among restoration actions in the short term (1–10 years). However, in the long-term, greater investment in regrowth projects yielded the largest restored land area using this criterion (Figure 4a). A similar pattern of relative outcomes from alternative investment scenarios occurred for floristic composition, although the absolute areas of land that satisfied vegetation quality thresholds were much lower (Figure 4c). For wood volume, vegetation quality criteria were typically only satisfied in the long term (15–27 years), after which the area reinstated to modest levels of vegetation quality (>50% of reference forest) was dominated by investment in planting (Figure 4b).

Accounting for preferences for certainty did not change the choice of restoration strategy but instead resulted in a modest reduction in the expected area of vegetation that exceeded minimum levels of vegetation quality (Figure 4). A difference in the outcome of strategies that favored investment in regrowth projects (as opposed to planting) was the large areas of managed land (funded projects) that failed to reach low levels of vegetation quality (i.e., 25% of reference forest). This was evident for wood volume and floristic composition, but was also the case for canopy cover when outcomes were constrained to the shorter time frame (Figure 4a–c).

## Discussion

### Restoration choices, risks, and trade-offs

Ecosystem restoration requires choosing among potential interventions. However, decision making is impeded by a lack of clarity around stakeholder preferences (attributes of the outcome that matter) and how they might influence expected restoration outcomes from alternative investment strategies. Our analyses have demonstrated how the relative efficacy of different investment strategies is determined by properties of the ecosystem, the restoration technique, and the decisionmakers. Given the realistic constraint of a fixed budget, we showed that the time preferences of decisionmakers, their choice of attributes to evaluate outcomes, and their desired levels of vegetation quality can all be major factors governing restoration "success," and these interact to determine the "best" investment strategy. In our case, investment strategies that favored one type of restoration action (i.e., not a mixed strategy) yielded maximum outcomes given decisionmakers' preferences.

 

**Table 2** Probability of reaching or exceeding minimum levels of vegetation quality given different restoration actions (self-organized regrowth or biodiversity planting) and time frames in the Australian Wet Tropics

| Vegetation attribute | Minimum desired vegetation quality (% of reference forest) | Probability of reaching or exceeding minimum quality within 1–10 years (T1) | | Probability of reaching or exceeding minimum quality within 15–27 years (T2) | |
|---|---|---|---|---|---|
| | | Regrowth | Planting | Regrowth | Planting |
| Canopy cover (%) | 25 | 0.33 | 0.93 | >0.99 | >0.99 |
| | 50 | 0.11 | 0.79 | 0.93 | >0.99 |
| | 75 | 0.03 | 0.61 | 0.77 | >0.99 |
| Wood volume ($m^3$/ha) | 25 | <0.01 | 0.21 | 0.17 | 0.99 |
| | 50 | <0.01 | 0.09 | 0.05 | 0.50 |
| | 75 | <0.01 | 0.05 | 0.02 | 0.08 |
| Floristic similarity to forest | 25 | 0.11 | 0.90 | 0.55 | >0.99 |
| | 50 | <0.01 | 0.17 | 0.04 | 0.44 |
| | 75 | <0.01 | <0.01 | <0.01 | 0.01 |

Outcomes that have a moderate (≥0.5) or high (≥0.9) probability of being realized are shaded light grey and dark grey, respectively.

Globally, tropical forest regrowth has a large, albeit sometimes unrecognized, potential for landscape-scale ecosystem restoration. Given enough time many such sites considered together can provide opportunities for substantial collective gains (Chazdon 2014). However, in terms of our decision framework, any choice of restoration investment strategy involves trade-offs between the area and quality of vegetation, especially for the outcomes of wood volume or floristic composition. When regional investment strategies favor regrowth but timeframes are short, a large proportion of the sites that were initially selected for management will only reach a low state of vegetation quality by the end of the planned restoration period (Figure 4). If the community has expectations of high quality short-term outcomes, negative public reactions could then deter investments, because management bodies could be criticized for spending money on apparently failed projects (Tulloch *et al.* 2015), even if outcomes that exceed quality success thesholds have occurred at the desired (and planned) proportion of all selected sites. To overcome this, planning of large scale, multisite projects could incorporate knowledge about trade-offs and adopt outcome monitoring coupled with contingency strategies to intervene at sites that are not on a trajectory toward achieving minimum quality thresholds. At the site level, the lower investment and slower development associated with regrowth places it at further risk of being aborted by individual landholders (Zahawi *et al.* 2014).

Optimal investments in biological conservation can also be influenced by decisionmakers' preferences for certain outcomes (Ando & Mallory 2012). For example, in the case of threatened species management in New Zealand, avoidance of projects with uncertain outcomes increased selection of expensive projects which in turn meant that more species were excluded from management and fewer species were expected to be safe from extinction (Tulloch *et al.* 2015). If a similar dilemma occurred in a restoration context, it would be necessary to ask how much uncertainty decisionmakers would be willing to accept in order to explore the possibility of greater gains (Failing *et al.* 2013). However, in our case study, the decision preferences for certain outcomes modestly influenced the expected area over which vegetation was restored, and did not affect the choice of investment strategy.

## Towards informed and strategic reforestation decisions

Solving real-world conservation and restoration problems is complicated by multiple competing values, which can lead to difficult trade-offs (Failing *et al.* 2013). Here we have provided a conceptual and analytical approach that prompts decisionmakers to define and reappraise their preferences for important attributes of the outcomes, to explore management options and their consequences, and to examine trade-offs. We believe that our basic scenario type approach will be instructive in establishing the important elements of restoration investment problems and clarifying expectations and value preferences of decisionmakers. It can be viewed as a standalone tool or a precursor to more technical optimization approaches that find solutions to resource allocation problems through mathematical formulation of restoration prioritization problems drawing on principles from systematic conservation planning (e.g., Wilson *et al.* 2011; McBride *et al.* 2010; Pouzols *et al.* 2012).

  

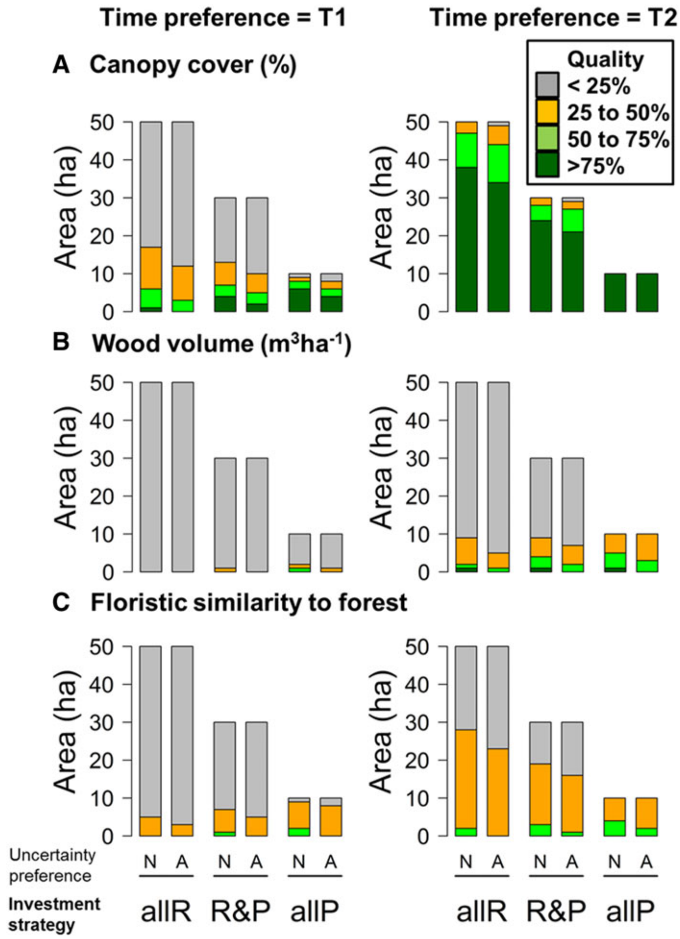


**Figure 4** Expected area restored to different levels of vegetation quality given differing timeframes (T1: 1–10 years; T2: 15–27 years), alternative investment scenarios (allR, all regrowth; R&P, regrowth and planting; allP, all planting) and preference for certain outcomes (N, neutral to uncertainty; A, averse to uncertainty). "Neutral" and "averse" scenarios were defined as a 50% or 90% chance of achieving prespecified outcomes, respectively. Shading of bars represents the area expected to reach different levels of quality relative to reference forest subject to the constraints of a fixed budget of \$500K and the specified allocation of budget between the two restoration actions.

The approach is flexible enough to accommodate different performance measures and management actions. We considered three performance measures and two management actions that represent extremes on a spectrum of passive to active restoration interventions. However, the approach could also incorporate other management options; for example, cheaper "industrial-style" timber/carbon plantation which are designed for rapid accumulation of wood volume. For other types of restoration, quantifiable attributes that indicate relevant outcomes could be substituted (e.g., population size of threatened species, water infiltration, fish stocks), and linked with relevant costed alternatives for management intervention. A next challenge will be to extend the approach to characterizing decisionmakers' actual preferences and/or indifference to attributes of outcomes (i.e., "multiple goods" Kahneman 1991) and to determine how this might affect resource allocation for restoration.

Regardless of the context, attributes are expected to differ in rate and certainty of recovery over time in response to different restoration actions. We recognize that our decision framework makes use of empirical data on vegetation recovery and uncertainty that, in practice, may not always be available. Our scenarios could inform new projects in the case study region but estimates would need to be assembled for other regions or ecosystem types. In some cases, data limitations might be addressed through interrogation of unpublished data sets. In the absence of evidence-based data, estimates could be generated using an expert elicitation process; but expert biases may reduce the reliability of any plans (Martin *et al.* 2012). More generally, increasing restoration effort in many places worldwide presents a timely opportunity for associated monitoring of different restoration actions to generate foundational data (Wortley *et al.* 2013) so that allocation of resources to future projects can be better planned.

Our quantitative evaluation of expected outcomes from restoration investment across multiple projects represents an improvement on subjective approaches typically used to guide resource allocation in direct payment schemes. It also provides a much needed mechanism to enable early, transparent evaluation of outcomes from policy instruments and environmental commitments under regulatory schemes. In particular, a realistic appraisal of outcomes can be used in conjunction with policy instruments such as biodiversity offsets, to assess the efficacy of the resources and timeframes proposed to compensate for losses in offset transactions (Moilanen *et al.* 2009; Curran *et al.* 2016). For example, in our case, even those investment strategies that utilized the most intensive and expensive restoration actions were unable to recover some of the more recalcitrant forest attributes within a quarter century. Likewise, expected outcomes benchmarked against environmental targets can be used to address tensions over rehabilitation responsibilities, enforcement and costs by determining in advance if or when restoration programs are likely to deliver outcomes that satisfy legal obligations stemming from development activities (e.g., mine site closure, Lamb *et al.* 2015; Ngugi *et al.* 2015).

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