**Chapter 3**

**Section A (conservation investment)**

**Introduction**

Global conservation funding is currently inadequate to eliminate biodiversity loss (Echols et al., 2019; Waldron et al., 2013). It 2016, investment into conservation was estimated to be $52 billion per year, yet it is further estimated that between $300 to $400 billion per year will be required to ensure healthy ecosystems across land- and seascapes (Huwyler et al., 2016). Although global estimates such as these are unlikely to be accurate, the order of magnitude conveys the scale of the funding challenge. Currently, the majority of conservation funding around the world comes from either government or philanthropic entities, where funds are distributed via grants (Huwyler et al., 2016; Larson et al., 2021). In response to the global climate and ecological crises, novel approaches to funding environmental projects (including projects related to climate change, biodiversity, and sustainable development) have emerged. These new mechanisms are largely focussed on leveraging private sector investment via conservation finance (Huwyler et al., 2016), green bonds, public-private partnerships, impact investing, and government-led incentives for private sector investment such as new policy, subsidies, loans, and risk mitigation mechanisms (Clark et al., 2018). It is hoped that these new approaches will affect both the quantity of funding available and the distribution mechanisms, moving away from short-term grants towards longer-term, sustainable financing (Echols et al., 2019). Although the development of alternative financing models for the environment is both necessary and promising, they are being developed within a global economy in which government policies, business models, and free-market capitalism still incentivise the environmental degradation the models are attempting to reduce (Clark et al., 2018). It is therefore likely that in the short- to medium-term, conservation practitioners will remain largely reliant on traditional grant-based funding to implement conservation activities.

Despite grant-based funding being the dominant mechanism for conservation investment, very little research has been done to assess the effects of unstable, non-linear budgets on biodiversity outcomes, nor the effects of alternative investment strategies. Given the lack of adequate funding for conservation, to have the greatest positive effect on biodiversity as possible, managers and conservationists need to ensure the investment of scarce resources is strategic and efficient, and they must strive to maximise the biodiversity outcomes of each dollar spent (Bruner et al., 2004; McBride et al., 2007; Waldron et al., 2013). Investing conservation funds strategically over time is made difficult when funding is based on short-term grants that generally last between one and five years (Hodge and Adams, 2016). Most conservation projects or initiatives, even in wealthy countries with relatively well-funded protected area networks, rely on such short-term grants to launch programmes, conduct research, and implement key activities such as training, engagement, enforcement, and outreach. This funding model results in long-term budgets that are non-linear, often unpredictable, and do not necessarily track changes in threat levels. The financial stability of a conservation project or organisation is therefore reliant on the ability to leverage external funding through grant applications, which are inherently competitive and have low success rates. This funding mechanism means that conservation projects go through periods of relative affluence when conservation activities (such as enforcement, policy interventions, and community engagement) can increase in scope and scale, ultimately leading to net benefits for nature. The same projects will inevitably go through periods of financial hardship, which often occur between grants. During these periods financial expenditure is restricted to minimal core activities, project activities wind down, staff redundancies occur, and initiatives end. These periods can have serious negative effects on conservation projects. Organisations lose talented staff and thus institutional knowledge, trust between stakeholders and the project or organisation can be lost as commitments may not be met, and stakeholders may view the project as unreliable due to inconsistent support. In many parts of the world where unregulated or illegal activities such as forest clearance and hunting of wildlife threaten conservation landscapes, periods of financial hardship can cause increases in these activities as project support for enforcement, engagement, outreach, and overall project visibility decreases.

The long-term cycle of organisations applying for grants to maintain budgets leads to ‘projectification’, whereby control over conservation activities, interventions, and strategic direction is ceded to funders, as conservation organisations adapt to funding trends and specific funder interests in an effort to remain competitive and maintain project funding (Hodge and Adams, 2016). There is also often a lack of transparency and coordination between funders and grant distributors which reduces cohesion and makes strategic allocation of funds at a broader scale difficult (Laufer and Jones, 2021). Nevertheless, many conservation projects are unable to fund activities through other means. Grants for conservation activities vary in size and duration, with larger, long-term grants (between three and five years) often requiring significant investments in staff time for the development of applications, and substantial administrative capacity to manage the grant if it is awarded. Such grants are often awarded by international financial institutions (e.g., the World Bank) or international development agencies (e.g., the United States Agency for International Development), and often come with complex rules governing procurement, accounting, reporting, and attribution (i.e., branding). These requirements often preclude smaller organisations that do not have in-house fundraising teams or large financial management and administrative capacity. Alternatively, conservation organisations can apply for smaller, short-term grants (usually between one and three years) which are often targeted towards specific species, habitats, or activities (e.g., the United States Fish and Wildlife Service Asian Elephant Conservation Fund, and the UK government’s Darwin Initiative). The smaller grants require less staff time for the application process and subsequent grant management yet can be limited in the amount of the award that can be spent on overheads, fixed costs, and other core project expenditure such as salaries, fuel, office space, and utilities. This results in the core operational budgets of smaller projects or organisations comprising small percentages of multiple short-term grants, leading to insecure and unstable core budgets that can fluctuate from year to year. Budgets such as this prohibit long-term strategic planning for investment of funds and conservation action (Emerton et al., 2006).

Reliance on limited duration grants rather than permanent core funding is one cause of the global conservation funding shortfall. Protected areas are the cornerstones of landscape-level conservation, yet up to 75% are severely underfunded (Coad et al., 2019). Insufficient funding of protected land- and seascapes leads to poor management, ecological damage, and the loss of species and habitats (Kearney et al., 2020; Pringle, 2017). It is difficult to design and implement effective conservation action that targets the correct drivers at the correct spatial and temporal scales when available funding is consistently below what is required (Tulloch et al., 2020). In landscapes where harvesting of wildlife occurs, weak management and regulation, which are common symptoms of chronic underfunding, can increase the probability of population collapse of the harvested species (Fryxell et al., 2010). In the absence of dramatic increases in funding and resources available to landscape managers, studies that explore the trade-offs between different strategies for investing existing resources will be critical. Site-level assessments of investment priorities are relatively common, and form an important part of a manager’s toolkit for developing strategy (see Ervin, 2003; Utami et al., 2020). Yet studies that provide broader theoretical insights into long-term investment strategies in the context of finite resources are lacking. There is a large body of literature that explores prioritising conservation investment over space, or the ‘conservation resource allocation problem’ (Wilson et al., 2006), with approaches including return on investment (Armsworth et al., 2018; Murdoch et al., 2010), heuristic algorithms (Meir et al., 2004; Wilson et al., 2006), regression models (Fishburn et al., 2013), and impact mapping (Tulloch et al., 2020). The next question, which is equally important yet largely unanswered, is once land has been selected or acquired for conservation, how should the authority responsible for its management invest finite conservation resources over the next five, ten, thirty, or fifty years to minimise biodiversity loss?

One of the main challenges associated with assessing future conservation implementation and predicting outcomes is the inherent uncertainty surrounding future conditions (McBride et al., 2007). Previous studies have investigated the effects of investment uncertainty (transaction uncertainty and performance uncertainty) on the optimal allocation of conservation funds to land acquisition (McBride et al., 2007), and uncertainty surrounding future site conditions (availability and ecological condition) and how this influences the optimal combination of short- and long-term conservation contracts with private landowners (Lennox and Armsworth, 2011). Yet the uncertainty surrounding changing social-ecological conditions within a single site or landscape over time, and how this may affect biological resources given different investment strategies by the management authority, has yet to be investigated. The global human population is increasing, particularly around protected areas and other ecologically rich landscapes (Wittemyer et al., 2008), and increasing human populations within these areas increase pressure on natural resources (Lindsey et al., 2014). Therefore, understanding how investment decisions by landscape managers affect system dynamics in the context of increasing human pressure and uncertainty will be critical for developing strategies that maximise conservation gains. Lessons can be learnt from empirical studies that examine past strategies and the subsequent observed outcomes (Santana et al., 2014), but using such data to project future social-ecological conditions and system dynamics is at best challenging, and at worst misleading (Mouquet et al., 2015). In contrast to empirical studies, simulation modelling offers an analytical environment within which system dynamics can be stress tested without any real-world consequences.

Conservationists have for many years relied on both theory and empirical generalisations to make urgent decisions when appropriate data have been lacking (Doak and Mills, 1994). Perhaps borne out of necessity in the past, theoretical models are now seen as important tools for ecologists and conservation biologists to improve understanding of their study systems (Green et al., 2005). Mathematical models offer the opportunity to take the well-studied component parts of a complex system and reassemble them in ways that capture their fundamental properties whilst allowing for the interrogation of system dynamics (Wilson, 1999). Such models require complex systems to be carefully simplified so that theories can be tested within a manageable environment whilst ensuring fundamental processes are honoured. The simplification of models to develop and test theory has been seen as an important approach for decades, with the understanding that building models that are all at once manageable, general, realistic, and precise is impossible (Levins, 1966). The importance and utility of simple theoretical models is easily forgotten in this age of exponentially increasing computing power and advanced statistical techniques, which allow researchers to move towards increasingly complex models and analyses. However, adding complexity and detail to models is not always the best approach as increases in complexity require more data and computation time, analysis and interpretation become more difficult, and the ability to generalise is lost (Green et al., 2005). Social-ecological systems (SES) are fundamentally complex, dynamic systems that are characterised by non-linear relationships and feedbacks between multiple social and ecological sub-systems (Berkes et al., 2000). It is implausible to build a model that captures all components of an SES, and therefore simplified models that simulate the fundamental dynamics are required to test social-ecological theory. Generalised Management Strategy Evaluation (GMSE) is a modelling framework that allows the construction of simplified social-ecological systems that are comprised of four fundamental sub-systems, allowing for a huge variety of theoretical investigations (Bunnefeld et al., 2011; Duthie et al., 2018).

In this study, we build a widely applicable mechanistic model of a generic conservation landscape and use it to investigate the dynamics between different conservation investment strategies and forest loss, in the context of finite resources and increasing human populations over a period of 50 years. To disentangle and emphasise potential effects of the different investment strategies on forest loss, we simplify the system so that the actions of the human stakeholders are the only factors influencing forest loss, and we push the investment scenarios to their extremes. We use the GMSE modelling framework (Duthie et al., 2018) to test the effects of five investment scenarios available to the landscape management authority that are designed to reflect real-world conservation funding scenarios: 1) a uniform management budget that does not increase or decrease over the study period, 2) a management budget that increases linearly over time, 3) a management budget that fluctuates in a predictable and regular way, reflecting short-term grant cycles, 4) a management budget that fluctuates randomly and unpredictably, but with only minor variation from the starting value, reflecting a core budget that increases or decreases via short-term grants, and 5) a management budget that fluctuates randomly and unpredictably with high variation from the starting value, reflecting a highly variable budget that has no core quantity, and is therefore entirely governed by short-term grants of varying sizes and durations. This modelling framework is generalised in such a way as to be of interest to landscape managers and conservationists around the world who are reliant on non-linear and unpredictable funding cycles, and offers theoretical insights into the consequences of the business-as-usual conservation funding mechanisms.

**Methods**

*GMSE*

GMSE is designed to simulate dynamic decision-making by stakeholders in a social-ecological system (Duthie et al., 2018). The stakeholders are a) the “manager” who represents an appropriate authority, for example a protected area manager or a natural resource manager, and b) the “users” who represent independent actors such as farmers or hunters. Additionally, there is a natural “resource” population, for example animals or trees, that requires management. In each simulation, the manager is attempting to get the resource population as close to a pre-determined value as possible, and the users are trying to maximise their utility on the landscape. Simulations in GMSE are comprised of four submodels that govern the social-ecological system, each of which can be individually parameterised (Figure 1). The submodels are (1) the natural resource model, which is used to simulate the biological population within the system. The natural resource model can simulate complex spatially explicit biological populations that have individual traits such as age, and population-level traits such as carrying capacity and related density-dependent mortality. Because individuals within the population have discrete traits, there is inherent stochasticity within the population. (2) The observation model represents the observation process, and the associated error, whereby the manager estimates the size of the natural resource population. The manager sets policy based on the estimates rather than the actual population size, thus introducing uncertainty that exists in the real world. The submodel has four methods available which mimic commonly used biological monitoring techniques. (3) The manager model uses the genetic algorithm (GA, see below) to develop management policies that attempt to reduce deviation of the natural resource population from the target population size. The manager achieves this by dynamically altering the cost of actions for the users thereby increasing or decreasing the ability of the users to act on the resources. (4) The user model, in which after the manager has set the policy, each user calls the GA to develop a strategy for that time step that maximises their utility (e.g., maximises their yield) given the constraints imposed by the manager. Users can choose to act on the natural resources (e.g., cull or scare), which can affect the resource population (e.g., if they choose to cull) or the landscape cell (e.g., if they choose to scare, forcing resources onto another cell). These changes then feed into the natural resource submodel in the next time step. For detailed explanations of the submodels, see Duthie et al (2018) and the documentation for the GMSE R package.

The primary approach to altering system dynamics is via the manager and user budgets. These parameters are relative rather than absolute and therefore the values are less important than the relationship between them. Generally, when the manager has a high relative budget, they have a greater ability to set policies that will influence the resource population in the desired way. For example, if the resource population is below the target, a manager with a relatively high budget can increase the costs of culling for the users, thus reducing the users’ ability to cull, and in turn allowing the resource population to recover. Conversely, if users have a relatively high budget, then they are more likely to be able to afford to take actions such as culling, even if the manager is setting the costs of such actions as high as possible. The budgets, and the associated dynamics, can be used to replicate various real-world systems and scenarios such as conservation conflicts, power dynamics, and lobbying (Cusack et al., 2020; Duthie et al., 2018; Nilsson et al., 2019).

*Genetic algorithm (GA)*

The GA is the core process by which the manager develops policy and users decide upon actions. The GA mimics the process of natural selection whereby each call to the GA results in several possible strategies being initialised. Multiple iterations then allow cross-over and mutation between the initialised strategies, ensuring that budgets are not exceeded. Each subsequent iteration of strategies is selected via a fitness function and a tournament. This process results in adaptive, but not necessarily optimal, strategies for the manager and the users. In each simulation time step the GA is called by the manager and each of the users to simulate decision-making. The GA first takes the manager’s budget constraints, user action histories, and the predicted consequences of each action on the resource population and develops a strategy for the manager to reduce deviation from the target resource population size. Once the manager’s policy is established, users will individually call the GA to decide upon actions that maximise their utility (e.g., agricultural yield). Users can choose from several options depending on the parameters set by the researcher. These include tending their crops or acting on the natural resources (e.g., cull, scare), all of which will have some effect on their yield. Their ability to act on the natural resource is governed by both the user budget, and the manager’s policy, in each time step.

Diagram

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**Figure 1. Conceptual flow diagram showing the four submodels and the genetic algorithm, and how they interact in a single time step in GMSE. Figure taken from Duthie et al., (2018).**

*Model parameterisation*

Landscape

In this study, we have used the GMSE modelling framework to explore the effects of different investment strategies and funding models available to a conservation manager on forest resources, in the context of finite funds and increasing anthropogenic pressure caused by an increasing human population. We simulated a forested landscape of 100 × 100 cells, where we assumed one cell was equivalent to 1 hectare, resulting in a landscape of 10,000 ha (or 100 km2). We allocated 30 “users” to the landscape, which in this case represented 30 villages or communities, each of which had an equal area of spatially explicit land upon which they could act. This resulted in each village having approximately 333.33 ha (3.33 km2) of land. We assumed the users represented agricultural communities whose primary livelihood is farming. We simulated scenarios over 50 time steps, which we assumed represented 50 years.

Resource population

The flexibility of GMSE allows for the biological resource to represent a population of a wide range of taxa. In this study we assumed the resources were trees, that the manager’s goal was to protect as many trees as possible from being felled (i.e., maintain the resource population at the starting value), and that the users were able to increase their agricultural yield by felling trees on their land. We tested the landscape with a tree density that was realistic for a tropical forested landscape (50 trees ha-1, n = 1,125,000), but because the number of users on the landscape was relatively low, due to each user representing a community rather than an individual farmer, the absolute number of trees felled was too low to see clear differences between scenarios. We therefore reduced the total number of trees to 100,000 to ensure trends in felling were clear to see. Trees were randomly distributed across the landscape, reflecting natural variation. The population dynamics of trees is difficult to capture over a 50-year time period due to slow growth and recruitment relative to animals. Furthermore, we wanted to eliminate any “noise” around the deforestation signal so that the only driver of forest loss was the effect of user actions on the trees. Therefore, despite high flexibility within GMSE for simulating realistic population dynamics, we removed the effects of natural recruitment or natural deaths (density-dependent and density-independent), resulting in a static population (excluding the effects of the users). If trees were present on a landscape cell, they reduced the agricultural yield that could be harvested by the user. Each tree reduced the cell’s yield by 8%, with the cumulative reduction in yield governed by the exponential function:

Where *y* is the yield of the cell when trees are present, *Yr* is the % reduction in yield for a single tree, and *Rt* is the number of trees remaining on the cell. Therefore, if there are 50 trees on a given cell, the cell’s yield is 1.5% of the total possible yield. If there are 25 trees remaining on a given cell then the cell’s yield increases to 12.4%, and so on.

Users

GMSE allows for each user to represent an individual actor or agent, who makes decisions about their actions based on individual circumstances. However, the number of users on a landscape cannot be changed during a simulation, and so to simulate increasing human populations we assumed that each user represented a village or community rather than an individual. We assumed that a population increase in a real-world community would result in increased human and financial resources, and increased demand for land (e.g., for housing and agriculture). These combined effects would increase the community’s desire and ability to clear forest land. This allowed us to employ the user budget to simulate population increases. The user budget is the primary parameter that governs a user’s ability to take actions, such as felling trees. Therefore, a user budget that increases during the simulation represents an increase in the user’s power to act, thus simulating population increases. The land ownership parameter for all simulations was set to TRUE, resulting in each community having a spatially explicit area of land upon which they could act. When users own their land, they use the GA to try and maximise their yield in each time step (rather than trying to increase their harvest of the biological resource, as is the case when land ownership = FALSE). The only actions the users were permitted to take were 1) tend crops, and 2) fell trees. The decision about which action to take in each time step was governed by trade-offs in cost versus benefit (computed within the GA). The parameter which defined how much a user could increase their yield by tending their crops was set to 0.01 (1%). This contrasts with the parameter governing the yield reduction for a single tree (8%, see section above). Different ranges of these parameters were tested for sensitivity (Supporting Information Figures S1a to S1d), with the final values chosen to deliberately ensure that felling trees would have a much higher positive effect on yield than simply tending crops. This was both to reflect the fact that in the real world expanding agricultural area will generally increase yield more than tending existing agricultural land, and to simulate strong exogenous drivers of deforestation that are found around the world, particularly in the tropics (Ceddia 2019, Davis et al 2015).

Manager

In our study, the manager represents a person or organisation that has a remit to conserve forest land and the authority to set and implement policy that affects the ability of users to take actions. We set the resource population target (which the manager tries to maintain) at the same value as the starting number of trees, and because there was no natural tree regeneration (natural population increase), the manager’s goal is to reduce forest loss as much as possible in every time step. These parameters were set to simulate a conservation landscape in which there is pressure on forest resources, and authorities are trying to eliminate, or reduce as much as possible, forest loss. This could, for example, represent a protected area which contains both forest and local communities. In each time step, the manager called the GA and identified a policy, which was reflected in the cost for users to fell trees, that attempted to reduce forest loss as much as possible. We assumed the manager’s budget reflected the actual budget of the authority, and could represent a monetary budget, available non-monetary resources (e.g., law enforcement resources), or a combination of these. In each of the different scenarios, the manager’s budget varied according to the funding scenario we were simulating. We assumed that the manager achieved perfect detection of resources, and so there was no error associated with the observation submodel. This was to keep the simulations as simple as possible. In the age of free, high resolution satellite imagery that is available every few weeks, it is not implausible that the manager has near-perfect deforestation detection over a landscape.

*Scenarios*

We designed 5 scenarios with dynamic manager budgets that simulated different funding regimes that a manager or authority with responsibility over a conservation landscape may encounter in the real world (Table 1, Figure 2). Scenarios 1 to 3 aimed to test three primary funding models and scenarios 4 and 5 aimed to test the effects of uncertainty and variability in funding. Before running the final 5 scenarios we tested several null scenarios to ensure the landscape was operating as expected (Supporting Information, figures S2a to S2c). Due to the nature of the GA (i.e., identifying one out of multiple possible near-optimal solutions), and that each actor on the landscape calls the GA in each time step, stochasticity in decision-making is explicitly built into the simulations. Therefore, each simulation was run 100 times to quantify variation in results. The manager budget, user budget, number of felling actions, the cost of felling actions, and the number of trees remaining at each time step were extracted for each replicate simulation. For each parameter, the 50, 2.5, and 97.5% percentiles across all replicates were calculated and used to represent the mean, and lower and upper confidence intervals, respectively. For all scenarios, we ensured that the total cumulative budget for the manager was equal across all scenarios (Table 1). This was to eliminate the possibility of one scenario outperforming another simply because the manager had access to a greater total budget over the simulation period. In all scenarios we assumed the same level of human population increase over time, and so for each scenario the user budget increases linearly with the same starting point and slope (Table 1, Figure 2). The absolute values for the user budget are arbitrary and can be set in such a way as to meet the objectives of the study. We tested various starting values and slopes for the user budget, increasing the parameter values until the absolute number of trees felled was sufficient to see clear differences between scenarios.

The manager and user budgets are not equal nor necessarily proportional, as they are used in very different ways (Duthie et al., 2018). Therefore, equal budgets (e.g., if both manager and user budgets were set to 500) do not necessarily equate to equal power to affect the system. The differences in manager and user budgets relative to each other is what governs the differences and changes in power to affect the system. It is important to recognise the incomparability between the absolute values of the manager and user budgets, and therefore to differentiate the two parameters in this study we will refer to the user budget as “community resources”.

All simulations were conducted using the R package GMSE (Duthie et al 2018, v0.6.2.0), and all associated analyses described below were conducted in R (v4.0.4, R Core Team, 2021). Relevant parameter values used in the simulations can be seen in the Supporting Information (section 3).

Scenario 1

This scenario assumed that the manager budget does not change over the simulation period (Figure 2). This scenario was designed to represent a conservation landscape in which the authority has a regular and predictable budget over time with which to invest in policy, but one which does not increase or decrease in response to changing threats or grant cycles. This scenario could represent a government-funded landscape which has a finite but regular budget that is not reliant on short-term grants.

Scenario 2

This scenario assumed that the budget available to the manager starts low but increases with increasing pressure on the landscape (Figure 2). This scenario could represent a statutory authority in a conservation landscape in which the authority is provided regular and predictable budget increases with which to invest in policy. In this scenario the management authority is not reliant on short-term grants. The shape of the manager budget (starting point, slope) was calculated to ensure that the total cumulative budget was equal to the other scenarios.

Scenario 3

This scenario assumed that the budget available to the manager increases and decreases in a regular and predictable way, regardless of the changing pressure on the landscape (Figure 2). This scenario was designed to replicate a conservation landscape in which the management authority is reliant on regular grant cycles. The scenario assumes that the authority conducts successful fundraising at regular intervals, and thus has a varying yet predictable budget with which to invest in policy implementation. The cycle length (i.e., the wavelength) is approximately 5 years, reflecting larger grants that are often provided by statutory funding agencies or international bodies. These large, longer-term grants require a high investment in staff time to apply for, and high administrative capacity to manage once implemented, and so are generally won by large, international organisations, government agencies, or collaborations between such partners, where the required resources already exist. To simulate this funding cycle, we produced a sine wave of the form:

Where *MB* is a vector of resulting manager budget values, and *t* is a vector of time steps (1:50).

Scenario 4

This scenario assumed that the budget available to the manager increased and decreased in unpredictable and irregular ways (Figure 2). This was to simulate a conservation landscape in which the management authority relies partly on grant funding for policy implementation, and so applies for a range of different grants which vary in size and duration but is not necessarily successful at any given time. This scenario assumes the management authority has some level of core funding, and so the budget never decreases to zero. This scenario could reflect any number of conservation landscapes around the world, where project budgets are subject to the success of funding applications, resulting in variable and unpredictable resources for project activities and policy implementation. To simulate this scenario, we produced a set of three sine waves by randomly sampling values between 0.01 and 0.08 for the fundamental frequency, between 1 and 5 for the wave frequency, between 1 and 150 for the wave strength (amplitude), and between 0 and 180 for the wave delay. The three sine waves were then combined using an Inverse Fourier Transform to produce a random complex wave (ref?). Each of the 100 replicates produced a different complex wave (Figure 2 shows 10 examples, see Supporting Information section 4 for all the waves used in the simulations). The Inverse Fourier Transform took the form,

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Where *trj* is the trajectory of the random complex wave, *acs* is the additive constant signal, *cs* is the component strength, *cf* is the component frequency, *w* is *2 × π × F0*, where *F0* is the fundamental frequency, *t* is the duration of the wave, and *cd* is the component delay.

Scenario 5

This scenario is a more extreme example of scenario 4 and aimed to test the effect of increased variation and uncertainty in manager budgets on deforestation and system dynamics. We increased the range of the available values from which the fundamental frequencies and component strengths for the three sine waves could be sampled from, thus increasing the potential amplitude of each wave, and making the changes in wave frequency more extreme (Figure 2 shows 10 examples, see Supporting Information section 4 for all the waves used in the simulations). To simulate this scenario, we produced a set of three random sine waves by randomly sampling values between 0.01 and 0.2 for the fundamental frequency, between 1 and 5 for the wave frequency, between values 1 and 300 for the wave strength (amplitude), and between 0 and 180 for the wave delay. The three sine waves were used to produce a new random complex wave for each replicate, using the same formula as in Scenario 4.

Standardisation

Manager budgets in Scenario 1 had a constant value which summed to 25,000 over the 50 time steps, and for scenarios 2 to 5 we standardised the manager budgets to 25,000, using,

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where *x* is the vector of manager budget values produced in the above sections.

Maximum harvest under maximum conflict

The maximum harvest under maximum conflict (MHMC) was calculated for each time step in each scenario to improve our understanding of the power dynamics between the manager and the communities. The MHMC is a single value for each time step that is based on the manager and user budgets at that time step. It is the maximum number of trees a user can harvest if the manager uses all their budget to reduce felling, and the user uses all their budget to fell trees. The manager uses 10 budget points to increase the cost of felling by 1. There is always a minimum cost of an action of 10. Therefore, the cost of an action for the user, assuming the manager is using all their budget to increase the cost of the action, will be,

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In the above, *nUA* is the number of user actions (i.e., the number of trees felled), *CR* is the community resources (user budget), and *MB* is the manager budget.

**Table 1. details of the five scenarios**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Scenario** | **Description** | **Manager budget** | |  | **Community resources** | | |
| **Starting value** | **Total cumulative budget** |  | **Starting value** | **Slope** | **Total cumulative resources** |
| 1 | Manager budget remains constant (i.e., does not increase) over time. Community resources increases linearly | 500 | 25,000 |  | 2000 | 75 | 191,875 |
| 2 | Manager budget increases linearly, reflecting a regular and predictable increase in resources over time. Community resources increase linearly | 126.9 | 25,000 |  | 2000 | 75 | 191,875 |
| 3 | Manager budget increases and decreases in a predictable way, reflecting reliable funding cycles. Community resources increases linearly | 499.3 | 25,000 |  | 2000 | 75 | 191,875 |
| 4 | Manager budget increases and decreases unpredictably, reflecting unreliable and unpredictable funding streams over time. Community resources increase linearly | Variable | 25,000 |  | 2000 | 75 | 191,875 |
| 5 | Manager budget increases and decreases unpredictably, reflecting unreliable and unpredictable funding streams over time. Community resources increase linearly | Variable | 25,000 |  | 2000 | 75 | 191,875 |

Chart

Description automatically generated

**Figure 2. Manager budgets and community resources (user budget) for the five scenarios. Scenarios 4 and 5 have a different manager budget for each replicate simulation, and so this figure shows 10 examples for each.**

**Results**

The parameter settings used in the simulations ensured that communities would try and fell trees, thus increasing their yield, if it was possible to do so given the policy set by the manager. The values and positive slope of the community resources ensured that communities had sufficient power to clear the majority of the forest by the end of the 50 time steps in all scenarios (Table 2). These extreme parameter settings resulted in clear differences in the deforestation trajectories between the scenarios (Figures 3 and 4).

*Scenarios 1 to 3*

Of the three primary funding models, scenario 1 was the most effective at minimising deforestation over the 50 time steps (Figure 3). In all time steps, excluding time steps 4 to 9, scenario 1 retained the highest number of trees. This is despite having a felling count that increased linearly throughout the simulation (Figure 5). The increasing felling count in scenario 1 resulted in the loss of trees accelerating over time (Figure 3). Conversely, scenario 2 had a decelerating felling count over time (Figure 5) as the manager budget increased, resulting in a deforestation rate that slowed over time (Figure 3). Nevertheless, the low starting manager budget values for scenario 2, which were lower than scenario 1 for the first half of the simulation period, resulted in higher deforestation overall (Figure 3). Scenario 2 performed worse than all other scenarios (including scenarios 4 and 5) for the first half of the simulation period (Figure S5a), highlighting the effects of chronic underfunding. The fluctuations in the manager budget in scenario 3 is reflected in both the rate of deforestation (Figure 3) and the felling count (Figure 5). During periods of high manager budget, the felling count and deforestation rate decreases, and during periods of low manager budget, the felling count and deforestation rate increase. Despite the peaks in manager budget in scenario 3 regularly reaching values much higher than the manager budget in scenario 1, this funding model had the worst outcome in terms of forest loss than scenarios 1 and 2 (Figure 3) and resulted in complete loss of forest cover (extinction) in 93% of simulations (Table 2). This can be explained by the felling count which shows that during periods of very low manager budget, the number of trees lost is between two and three times greater than any point in scenarios 1 and 2 (Figure 5).

*Scenarios 4 and 5*

Scenarios 4 and 5 showed the potential effects of unpredictable and uncertain funding models on forest loss. Scenario 4 had less variation in manager budgets than scenario 5, and the simulations were much more likely to retain more forest cover than scenario 5 (Figure 4) across the 100 simulations. Interestingly, deforestation rates for scenario 4 were very similar to those of scenario 1, and scenario 4 outperformed scenarios 2 and 3 in most cases (Figure S5a). This suggests that unpredictable variation in manager budgets is not necessarily catastrophic, provided fluctuations are small and that some level of core funding means that manager budgets do not drop too low (Figure 2). Scenario 5 showed that large uncertainty and variability in manager budget could have very serious negative effects on forest cover over time (Figure 4). Despite many of the scenario 5 replicates having very high peaks in manager budgets (Figure 2), most simulations resulted in a worse outcome than scenario 4 in terms of forest cover. Of the 100 simulations, extinction occurred 25 times (25%) in scenario 5 (Table 2). As with scenario 3, the driver of forest loss can be seen in the felling counts for scenario 5, which reach extremely high levels during periods of low manager budget (Figure 5).

*Maximum harvest under maximum conflict (MHMC)*

The MHMC calculations revealed some of the power dynamics within each of the scenarios (Figure 6). The maximum number of trees that the communities could fell at a given time step decreased over time in scenario 2, reflecting the increasing manager budget that provided increasing power to the manager to set policy and affect the number of felling actions. The rate at which the MHMC value decreased in scenario 2 was itself decreasing, stabilising to a near-constant rate by the end of the simulation period. This reflects the increases in community resources over time, which were increasing at a faster rate than the increase in the manager budget (Figure 2), resulting in decreasing power for the manager. Scenarios 1 and 4 had the most stable MHMC values, reflecting the relatively stable manager budgets. The MHMC values for scenarios 3 and 5 reflected the fluctuating and highly variable manager budgets and demonstrated how the rate of forest loss could increase during periods of low manager funding. When the manager had little funding there was an increase in the potential number of trees the communities could fell, assuming the manager was using all their budget to reduce felling and the communities were using all their budget to fell trees (Figure 6).

Chart, line chart

Description automatically generated

**Figure 3. The number of trees remaining at each time step for scenarios 1, 2, and 3. Solid lines and faded ribbons are the 50, 2.5, and 97.5 percentiles from the 100 runs, respectively.**

Chart

Description automatically generated

**Figure 4. The number of trees remaining at each time step for scenarios 4 and 5. Solid lines and faded ribbons are the 50, 2.5, and 97.5 percentiles from the 100 runs, respectively.**

Chart

Description automatically generated

**Figure 5. The count of felling actions taken by all communities at each time step for the five scenarios. Solid lines and faded ribbons are the 50, 2.5, and 97.5 percentiles from the 100 runs, respectively.**

Chart, histogram

Description automatically generated

**Figure 6. Calculated maximum harvest under maximum conflict (MHUMC) for all five scenarios. MHUMC is calculated using: community resources / ((manager budget/10) + 10). The value is the maximum number of trees that could be felled if the manager was using all their available budget to prevent felling, and the community were using all their available resources to fell trees. The lines for scenarios 4 and 5 (which had different manager budgets for each replicate simulation) represent the mean MHMC value at each time step across all replicate simulations.**

**Table 2. Summary of the number of trees remaining at time step 50 (2.5, 50, 97.5 percentiles), and the number of extinctions, from the 100 replicates for each of the five scenarios.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Scenario | Trees remaining after 50 time steps | | | complete forest loss (in %) |
| Mean | 2.5 percentile | 97.5 percentile |
| 1 | 5857 | 4660 | 6412 | 0 |
| 2 | 715 | 281 | 1202 | 0 |
| 3 | 0 | 0 | 0 | 93 |
| 4 | 2823 | 545 | 5152 | 1 |
| 5 | 8 | 0 | 4159 | 25 |

**Discussion**

Global funding for nature conservation is far below what is required (Freeling and Connell, 2020; Laufer and Jones, 2021), and the funding that is available is rarely stable or sustainable over periods of more than a few years. To maximise conservation gains it is necessary to provide conservation managers, and conservation funders, with insights into the trade-offs between different approaches to long-term investment of limited resources in the context of increasing anthropogenic pressure on natural resources. To our knowledge, no studies have investigated the potential long-term consequences of existing funding mechanisms for conservation projects and organisations. Our results therefore provide crucial theoretical insight that funders, conservation bodies, and landscape managers can use to develop more effective long-term investment strategies.

*Primary scenarios (scenarios 1 to 3)*

Our results have demonstrated that in a situation where human pressure on a landscape is increasing over time, and assuming managers across all scenarios have access to the same total budget, the most effective funding strategy for a conservation manager is a stable, predictable budget. A constant budget is preferable to an increasing budget that starts too low, even when that budget increases beyond the value of the stable budget halfway through the study period. If a manager’s budget is too low at the start of the study period, initial forest loss is very high. The manager is able to reduce the rate of forest loss as their budget increases over time, but they are not able to make sufficient gains over 50 years to render the strategy better than a stable budget. Likewise, a fluctuating manager budget that reflects predictable grant cycles performs worse over 50 years than a stable budget. During periods of high budget, managers can develop effective policies that reduce forest loss. However, these periods are not sufficiently long, and budgets not sufficiently high, to offset the damage that is done during periods of low funding. Furthermore, the rate of forest loss during periods of low funding increases over time, as community resources increase. If the manager was focussed on the conservation of a wildlife population that exhibited reproduction and thus population growth, the periods of high budget, and therefore more effective protective policies, may be sufficient to maintain a healthy population as there would be periods of recovery. However, we assumed that the loss of primary forest could not be effectively reversed within a period of 50 years (refs). These simulations could be further parameterised to include realistic forest regrowth or regeneration based on a specific landscape or ecosystem, but this would decrease the generality of the results and therefore was not attempted here.

Providing a manager with a stable budget that allows the development and maintenance of policies that minimise deforestation over the long-term is the best approach. Stable, predictable budgets in the real world allow conservationists and landscape managers to maintain staffing levels, invest in long-term relationships and partnerships with stakeholders, maintain enforcement levels, and design policies and interventions that are strategic and adaptive over periods greater than short-term grant cycles. Conservation projects that are initially underfunded yet receive increasing resources will still spend many years working to reach the same levels of protection as they would have had, had they been provided an adequate, stable budget at the start. Our results predict that it could be several decades before the deforestation trajectories of the two alternative projects meet, and the increasing budget starts to pay dividends. Projects that repeatedly experience severe funding shortages due to grant cycles will not have the same capacity for long-term investment and strategic planning as projects with stable funding, resulting in greater losses for biodiversity.

*Uncertainty and unpredictability in funding*

Scenarios 4 and 5 highlight two common funding situations for conservation organisations and projects. Scenario 4 represents a situation where the management authority has some level of core funding that ensures the operational budget does not drop below a certain level, despite budget uncertainty over time. This is a common scenario for large, international conservation organisations or statutory authorities, which have long-term support for core operational budgets. They can increase their budgets at any given time through grant applications which can be used to support existing activities, initiate new programmes, bolster enforcement, or extend engagement and collaboration with stakeholders, all of which will have a positive effect on biodiversity conservation on the landscape. Likewise, grant funding will inevitably end within a few years, and there is no guarantee that future bids will be successful, resulting in decreases in overall budgets. However, the maintenance of budgets above a certain level means that core conservation activities do not cease, and the manager is able to minimise forest loss to a level similar to the manager in scenario 1. Conversely, scenario 5 represents a situation where the management authority has no core budget and is therefore entirely reliant on uncertain and unpredictable grant funding over time. This is the reality for many small organisations, grass roots projects, or poorly supported statutory authorities which rely on the ability of other partner organisations to leverage external funding. In this study, the manager in all scenario 5 replicates has the same cumulative total budget over the 50 years as the other scenarios, yet the shape of the budget curve is random. This leads to large and highly unpredictable positive and negative peaks in some cases. Our results show that there is large variability in the overall success of the manager in scenario 5 to minimise forest loss. In some cases, they can maintain a forest loss trajectory similar to scenarios 1 and 4, yet more often the rate of forest loss is worse, regularly leading to extinction.

The results from scenarios 4 and 5 translate logically to the real world; if a conservation project or organisation has no core budget support, it is entirely reliant on the success of fundraising efforts. Winning sufficient funding via short-term grants to support adequate long-term conservation management is neither reliable nor straightforward. When long-term budgets are unpredictable, uncertain, and highly variable, landscape managers are often unable to maintain core activities, guarantee continued support for communities and other stakeholders, plan investments strategically, or target investments at the most relevant drivers of biodiversity loss. In contrast, when core budgets are guaranteed, managers can maintain core activities and investments over the long-term which provides stability and minimises biodiversity loss.

*Key messages*

We have demonstrated that the dominant funding mechanism for conservation in the world today – the short-term grant cycle – is not optimal for conservation investment within social-ecological landscapes where there are competing objectives and increasing anthropogenic pressure on natural resources. In circumstances where project budgets experience negative peaks caused by gaps in grant funding, and where there is no core budget, biodiversity loss is accelerated. In these circumstances, managers are unable to maintain power to affect the system or set policies that benefit nature over the long-term. Increased uncertainty and variability around the shape of fluctuating budget curves inevitably increases uncertainty around the state of biodiversity over the long-term. Brief periods of high budgets in the grant cycle scenarios result in only brief periods of success where rates of forest loss decrease, and in the context of increasing human pressure on the landscape, these are insufficient to mitigate for the periods of low funding. Chronic underfunding, particularly in the early stages of a landscape conservation programme, can lead to serious negative effects on natural resources. Severe forest loss at the start of a project period, with all the associated losses of biodiversity, ecosystem process and services, leads to very poor project success over a 50-year period. Even when project budgets increase over time, the damage caused during initial periods of underfunding is difficult to remedy.

Simulation studies allow us to investigate possible biodiversity outcomes from a variety of scenarios over time periods much longer than for which we generally have empirical data for. Monitoring data for conservation projects rarely exist over timeframes as long as 50 years, and managers are therefore required to assess conservation actions using monitoring data from significantly shorter periods. This study has demonstrated that this can be misleading. For example, if a manager was provided forest monitoring data for scenario 3 between years two and six, or between years 14 and 18, it would be reasonable to conclude that the existing investment strategy and associated conservation interventions were working, as the rate of forest loss was decreasing. If a manager was given forest monitoring data from any four-year period from scenario 1, they could reasonably conclude that the investment strategy and associated conservation interventions were not working, as the rate of forest loss was increasing. Neither manager could be justifiably criticised for their inference; they are drawing conclusions from the best available data, which is what conservationists around the world must do every day. Nevertheless, our results have demonstrated that these inferences are likely flawed, and that the manager from scenario 1 will have greater success in minimising forest loss over the long-term if they maintain their strategy.

*Conclusions – what can be done?*

The global conservation community requires a huge increase in funding if it is to halt the decline in biodiversity and minimise the worst impacts of climate change (Echols et al., 2019; Larson et al., 2021). We have demonstrated that a funding model that relies on short term grant funding, which is a common mechanism in the conservation sector, is unlikely to be the most effective way of financing landscape conservation. In addition to the landscape-level challenges of short-term grants that we have demonstrated here, the lack of communication, cohesion, and national, regional, and global coordination between funders that administer conservation grants results in poor strategic allocation of funding across larger spatial scales (Laufer and Jones, 2021). Greater coordination between funders, or indeed less reliance on numerous, disparate funders, will allow more thoughtful and strategic assessments regarding allocation of conservation funds, thus maximising environmental return-on-investment (Echols et al., 2019). If global funding for conservation increases, the mechanisms by which this funding is distributed need to be carefully considered to ensure biodiversity gains per dollar are maximised. Our results suggest that simply increasing the number of short-term grants available within a competitive application framework is unlikely to provide the maximum gains. Alternative funding mechanisms are needed which provide stable and predictable budgets over multi-decadal timeframes thus allowing organisations and authorities to devise and implement strategic, long-term interventions and policies that benefit nature and people.

There is a wide range of funding sources available to conservationists, yet government and philanthropic sources are the most common (Clark et al., 2018). The fragility of government funding has been exposed during the Covid-19 global pandemic; around the world there have been shrinking national economies, dramatic increases in emergency government spending, and governments forced to prioritise sectors of the economy for support and recovery (Evans et al., 2020). Despite the irony, a global pandemic that was most likely caused by overexploitation of the natural environment (Lytras et al., 2021), is likely to cause a decrease in government spending on conservation, at least in the short term (Corlett et al., 2020; Evans et al., 2020). There is increasing recognition that broadening the sources of conservation funding is necessary to both increase global spending on the environment and to diversify the sources, thus stabilising funding against inevitable future economic shocks (Echols et al., 2019).

There are numerous sources of funding that are available for conservationists to explore. Funding for the environment from philanthropic entities is increasing (Gruby et al., 2021), and the influence of private foundations is growing (Betsill et al., 2021). As independent organisations, foundations have the potential to adapt their funding strategies and mechanisms to maximise effectiveness. If conservationists can provide evidence to support certain investment strategies, private foundations and other philanthropic entities are theoretically able to adapt accordingly. The idea of charitable giving that is evidence-based and results-orientated is already growing with the social movement known as ‘effective altruism’ (Freeling and Connell, 2020), giving the conservation sector an opportunity to shape the charitable funding landscape using empirical evidence. Global environmental agendas have driven the creation of global funds such as the BioCarbon Fund managed by the world bank ([www.biocarbonfund-isfl.org](http://www.biocarbonfund-isfl.org/)), the Global Environment Facility ([www.thegef.org](http://www.thegef.org/)), and the Green Climate Fund (www.greenclimate.fund), all of which are large enough to operate at a variety of spatial and temporal scales (Clark et al., 2018).

Arguably the most promising avenue for environmental funding is private finance, the power of which is yet to be fully realised (Clark et al., 2018). This is largely because the environmental sector has thus far failed to provide projects that are investable, scalable, and low risk (McFarland, 2018). Leveraging of private sector finance is increasing, and is being achieved through a variety of mechanisms including 1) national development banks which provide credit and finance to underfunded areas of society (Torres and Zeidan, 2016); 2) blended finance, which combines public and private finance through traditional mechanisms such as public-private partnerships, and through more novel mechanisms including development finance institutions (Clark et al., 2018); 3) custom-built partnerships between the private sector and governments, civil society, and non-governmental organisations, for example the Tropical Landscapes Finance Facility ([www.tlffindonesia.org](http://www.tlffindonesia.org/)) which provide long-term financing to support sustainable land use; 4) green bonds, which raise funds for projects that contribute to a more sustainable economy and deliver benefits to the environment (Sachs et al., 2019), 5) conservation finance, which is a broad term that describes financial solutions that deliver conservation gains *and* financial return for investors. An undeveloped field, conservation finance has huge potential as a private sector investment opportunity that delivers conservation goals, using mechanisms such as substitute funds, marine protected area bonds, and conservation impact bonds (Huwyler et al., 2016); 6) carbon market instruments such as REDD+ and the Green Climate Fund (Sachs et al., 2019); 7) other ‘green finance’ mechanisms such as impact investing, fiscal policy, green central banking, and community-based green funds (Sachs et al., 2019).

Although in relative infancy, private sector investment for conservation and the environment is underway, with global players in both conservation and finance recognising the potential. An example is the NatureVest collaboration between The Nature Conservancy and JP Morgan Chase which focusses on identifying and financing investable projects that deliver for investors and the environment (Kaiser, 2015). To successfully leverage private sector finance, the conservation sector (and the environmental sector more broadly) needs to dramatically increase the number and scale of projects that have low-risk rates of return and conservation impacts that are clear and measurable, thus making them attractive investments.

There is currently a large gap between the global ambitions for environmental recovery and the money available to fulfil those ambitions. In this study we have demonstrated that stable, long-term funding is more effective for the management of social-ecological landscapes than short-term, unreliable grant funding. Yet funding streams that provide such long-term financial stability are rare. Increasing the quantity of funding available for conservation and moving towards more sustainable investment strategies is going to require paradigm shifts across national and global policies and economies. If the conservation sector wants sufficient and sustainable funding, we will need to embrace new, creative ideas and form novel collaborations and partnerships to unlock the private sector and leverage such funding within the private sector investment framework.