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The influence of discounting ecosystem services in robust multi-objective optimization – An application to a forestry-avocado land-use portfolio

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ABSTRACT

Discounting is standard in economics to consider time preferences of people and account for future market changes. However, so far discounting has mainly been applied to monetary flows and ignored for many ecosystem services. In multi-objective optimization, selectively disregarding time preference for some non-monetary services create bias. Here we study how discounting a range of ecosystem service indicators influences a public planner's optimal land allocation. We used a robust multi-objective optimization approach to model a mixed forestry-avocado farm portfolio in South Africa. The objectives for optimization were the provisioning of various ecosystem services and disservices represented by four indicators: net present value, payback period, carbon sequestration, and fertilizer use. To account for time preferences concerning indicator flows, we applied specific discount rates to each ecosystem service indicator, depending on its character (non-monetary or monetary indicators). We demonstrate that discounting reduces the standard deviations of the discounted sum of the indicators, which leads to less diversified land-use portfolios. To account for discount rate uncertainty, we introduced three indicator sets simultaneously, each using a different discount rate, which was off setting the effect of decreasing diversification.

1. Introduction

Discounting is used to express how people value receiving a benefit or incurring a cost sooner rather than later (time preference), as well as to account for factors like risk and inflation. In forestry, when to apply discounting and how to select a discount rate are subjects of long-standing controversy, since small changes in the discount rate can strongly impact outcomes over the remarkably long timelines used in forest management planning: as Samuelson (1976) notes, "the positive interest rate is the enemy of long-lived investment projects" (p. 473). In forest economics, discount terms are commonly applied for net benefit flows when computing standard financial indicators like the net present value (Assmuth et al., 2021; Lessa Derci Augustynczik et al., 2020; Müller et al., 2019; Parkatti and Tahvonen, 2020; Radke et al., 2020; Tahvonen et al., 2010). In addition to financial indicators, modern forest management planning also aims to incorporate a range of non-financial objectives, for example the provisioning of non-market ecosystem services, into decision frameworks. However, the indicators associated with these non-financial objectives are rarely discounted unless their value can be reliably expressed in monetary terms (Friedrich et al., 2021; Knoke et al., 2020b; Kolo et al., 2020). Consequently, time preferences regarding non-monetary costs and benefits are routinely ignored by multi-objective decision support tools (Baumgärtner et al., 2015; Drupp, 2018; Gollier, 2010; Traeger, 2011; Weikard and Zhu, 2005). We argue that one could nevertheless use the biophysical goods and services directly as a measure for the benefits or costs they provide or cause. Then the service indicators could serve as the numeraire which contributes directly and not via any associated cash flows to the utility function of the beneficiaries (Drèze and Stern, 1987). Just a few studies already consider time preferences for non-monetary ecosystem service indicators (Juutinen et al., 2014; Mazziotta et al., 2016).

Far from being the exclusive domain of economists, inter-temporal trade-offs are fundamental features of decision contexts in environmental management and sustainability. Past work on multi-objective decision support often takes as a decision variables the economic value of ecosystem services. This might be done, for instance, by

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multiplying units of carbon sequestered by a carbon price (Plantinga and Birdsey, 1994; van Kooten et al., 1995), while more recent studies extended the scope to include carbon storage in living trees, deadwood, and harvested wood products (Assmuth et al., 2021, 2018; Pihlainen et al., 2014). However, in the absence of established, well-functioning markets for other ecosystem services, valuation can be challenging and prices are often difficult to forecast. We were only able to identify a handful of examples in the research literature where the future provision of biophysical indicators was discounted, with carbon sequestration being the most prominent (Johnston and van Kooten, 2015; Juutinen et al., 2014; Mazziotta et al., 2016; Timmons et al., 2016; Yousefpour et al., 2018). However, these studies do not use discounted biophysical indicators as decision variables, rendering optimal solutions sensitive to price uncertainty. Here, we describe an alternative approach that uses discounted biophysical indicators (e.g. periodic net carbon sequestration) as decision variables to avoid commingling ecological projections with economic ones.

The rationale of discounting carbon is admittedly straightforward: nature-based solutions may prematurely release carbon following natural disturbance (risk), and the possible emergence of climate-destabilizing feedback loops makes near-term sequestration greatly preferable to postponed sequestration (time preference) (Johnston and van Kooten, 2015; Schlamadinger and Marland, 1999). While its much-discussed commodification and the emergence of offset markets (Button, 2008; Dalsgaard, 2013; Gifford, 2020) makes carbon somewhat unique, there is no clear reason why discounting other non-market ecosystem services flows could not be similarly integrated into multi-criteria land-use planning (Cohen et al., 2020), although appropriate social discount rates may be needed as discussed below (Price, 1988). In fact, accounting for time preferences for some objectives while disregarding it for others may distort the results of multi-objective optimization studies by making discounted financial flows appear smaller relative to aggregated non-financial ones (Kula and Evans, 2011).

For public planners, determining appropriate discount rates for assessments involving public goods and common-pool resources is a familiar and recurring problem, even when economic values for non-market goods and services can be reliably estimated (Price, 1988). In selecting a discount rate, public planners must balance present demand against the needs of future generations (Addicott et al., 2020). Because methods used to derive descriptive discount rates for private goods are often not applicable, social discount rates may be used in their place to enable cost-benefit analysis for long-term investments designed to generate public benefits. The protocol for determining the correct social discount rate is debated and likely context dependent (Abelson and Dalton, 2018; Drupp et al., 2018). In the forestry context, social discount rates are typically lower than private ones, so the use of social discount rates can suggest longer rotations or larger investments in forest management (Muñoz Torrecillas and Cruz Rambaud, 2017; Price, 1988).

Baumgärtner et al. (2015) argue that ecosystem services should be discounted at significantly lower rates than consumer goods in a global context characterized by growing commodity consumption and declining ecosystem services provisioning. Future scarcity of a good or service associated with limited possibilities to substitute this service influence discount rate settings, especially for ecosystem services (Drupp, 2018). Thus, dual discounting offers a possible solution for public cost-benefit analysis. Following a Ramsey-like discount rate model, a robust definition of socioeconomic contributions to discount rate estimates would ideally consider probabilistic developments of population, economic growth, and emissions (Rennert et al., 2021). Discount rates therefore mimic not just pure time preferences in a Ramsey approach, but furthermore anticipate future developments, and are thus highly associated with uncertainty.

Here, we explore how discounting non-financial ecosystem services influences a simulated land allocation optimization from a public planner's perspective. We address the aforementioned discount rate uncertainty by introducing a set of discount rates considered simultaneously within our optimization scenarios, taking as our starting point a social discount rate typical for South Africa (Addicott et al., 2020). Using a multi-objective robust optimization model, we compare two strategies: using just a single social discount rate for monetary variables versus implementing ecosystem service-specific discount rates. Because discounting is closely linked to uncertainty, our approach explicitly accounts for uncertainties in future provision of ecosystem services (Knoke et al., 2017). Our study analyses the influence of 1) considering decision-makers' time preferences for all ecosystem services consistently and 2) using ecosystem service-specific discount rates on land allocation in a multi-objective robust model.

The research questions, guiding our study, are:

- How does discounting change the evaluation of benefits and costs related to ecosystem service indicators?
- How does discounting of benefits and costs related to ecosystem services change the composition of robust multi-objective land-use portfolios?

2. Methods

Our study simulates land-use management in the province of KwaZulu-Natal, South Africa. In recent years, forestry plantations in this area have been increasingly converted to agricultural land uses, which are seen as more profitable (Hitayezu et al., 2016). Whereas agriculture with cash crops promises high monetary returns, forestry provides long-lived wood products, which can be of high interest for long-term carbon sequestration. Conversely, the greenhouse gas emissions produced by Africa's agriculture are among the fastest growing emissions in the world (Tongwane and Moeletsi, 2018). Decision-makers have to face trade-offs between financial and non-market indicators to fulfill private and public demands on land-use management (Groot et al., 2018), while water use policies in South Africa restrict highly productive land-use options. Land may provide multiple public goods and services. However, worldwide large parts of land are privately owned by farmers, enterprises, or land-use managers whose decisions and motivations shape our landscape (Lowder et al., 2016).

A public planner's optimization of land-use allocations on farm level could include both farmers' private and social interests (Gosling et al., 2021; Reith et al., 2020) and consider the growing demand for multi-functional management on scarce land. We therefore set our example of a public planner in a country where limited availability of productive land generates a high interest in optimized land utilization. By including time preferences for ecosystem services, we account for the increasing demand for short-term approaches to improve environmental quality, measured by indicators for carbon sequestration and use of fertilizers. We simulate as baseline investment periods of 46 years for six different land-use types consisting of forest stands of pine and eucalyptus (two consecutive forest rotations of 23 years each), as well as avocado fruit orchards (See Table 3).

To study the impact of discounting on the performance of ecosystem service indicators, we compare discount rates from 0 to 3% (RQ1), without distinguishing between specific ecosystem services. To analyze how changing discount rates impacts optimal forestry-avocado land-use portfolios, we use ecological discount rates ranging from 0 to 3%, with each rate being one percentage point lower than the corresponding social discount rates we apply to financial flows (RQ2) (Baumgärtner et al., 2015; Drupp, 2018). This is an example of *dual discounting*, an approach that has been recommended for public cost-benefit analysis involving uncertainties about future prices for environmental services or the relative shortages between different goods over time. For goods with differing consumption growth and varying elasticity of marginal utility, dual discounting accounts for opposite future market conditions (Baumgärtner et al., 2015). In the following section, we introduce our modelling approach and related input data (Fig. 1).

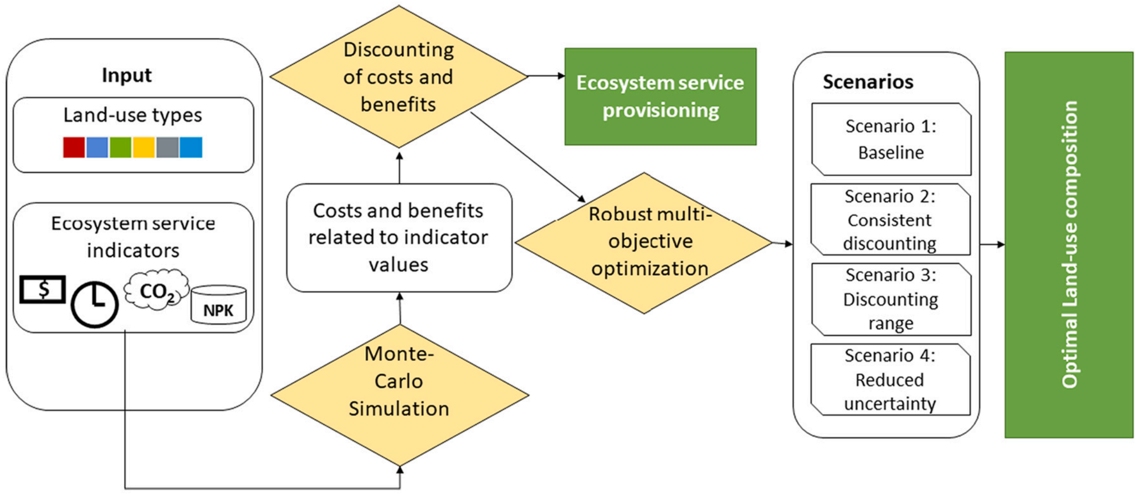

Fig. 1. Illustration of the simulation concept.

2.1. Discounting of costs and benefits related to ecosystem services

Our general model is described with formula (1). Analogous to the net present value as a sum of cash flows, we calculated the sum of yearly ecosystem service flows for each considered land-use type. We discounted the yearly costs and benefits of each of the ecosystem services depending on their time of occurrence for every land-use type. We used a set of varying discount rates, evolving from a country-specific social discount rate of 3% as baseline for the socio-economic indicators (Addicott et al., 2020). When including both market and non-market ecosystem services we used a discount rate specific for ecosystem service-related costs and benefits (Baumgärtner et al., 2015; Drupp, 2018) to directly discount the biophysical indicator units. This "ecological"discount rate for non-market ecosystem services was set at one percentage point below the corresponding social discount rate. We summed up the yearly discounted changes of ecosystem service provisioning over the entire investment period with formula (1).

$$E_i = \sum_t e_{i,t} \times \omega^t \text{ with } \omega = \frac{1}{(1 + r/100)} \quad (1)$$

E_i, Sum of discounted costs and benefits of ecosystem service i;$e_{i,t}$, Costs (=disservices) or benefits (=services) related to ecosystem service i at time t [depending on the nature of the service either in monetary or biophysical units];

r, Ecosystem service specific discount rate $r \in (0, 1.0, 2.0, \ldots, 10.0\%)$.

2.2. Robust multi-objective optimization approach

We combine a robust optimization model and a multi-objective approach to simulate optimal land allocations (Knoke et al., 2020c). Our model, formulated as a Min-Max problem (Romero, 2001), allocates land shares to various land-use types to minimize the non-achievement across all four objectives and uncertainty scenarios simultaneously. The predefined land-use types are decision alternatives, while the area allocated to these land-use types is our decision variable (Knoke et al., 2020c). The decision variables refer to the proportion (0–100%) of the total area allocated to each land use; the sum of all the shares must equal 100%. Based on the decision-maker's preferences and level of uncertainty tolerance, the model optimizes the land-use type composition to offer the best compromise (Gosling et al., 2021). The resulting land-use allocation improves achievement levels for all indicators by balancing the relevant decision criteria.

To represent our missing knowledge about future developments, we define discrete uncertainty scenarios, based on all systematical combinations of the best and worst cases for each indicator and each land-use type (Gorissen et al., 2015). These uncertainty scenarios form the surface of the uncertainty spaces for each ecosystem service indicator. Uncertainty spaces of different size account for different expectations about the future; the larger the uncertainty space, the more pessimistic a decision-maker is about the future. Therefore, we mimic potential variability among decision makers (Knoke et al., 2020c) by choosing different uncertainty factors ($m \in (0, 1.0, 1.5, \ldots 3.5)$). The mathematical formulation of the uncertainty settings is provided in the appendix.

Models for land-use decisions mostly assume uncertainty-averse decision-makers (Bezabih and Sarr, 2012). However, given the potentially diverse circumstances and backgrounds of different decision-makers, including several uncertainty profiles for different social groups might be useful. For example, women in developing countries, who often control food production on small-scale farms, tend to be more uncertainty-averse (Hitayezu et al., 2016; Villamor et al., 2014). Moreover, farm size is linked to available investment capacity, which along with demographic variables like educational attainment, influences the uncertainty preferences of the owners (Hitayezu et al., 2016; Reyes et al., 2021). By introducing several levels of uncertainty aversion, we represent different hypothetical groups of decision makers. Smaller uncertainty factors ($m = 1$) represent decision-makers with low uncertainty aversion, while higher values ($m = 3$) indicate higher uncertainty aversion. For $m = 0$ we assume uncertainty-neutral deciders as the model ignores uncertainty by only using the expected values (Gosling et al., 2021).

We weight all objectives and their related indicators for each discount rate equally and incorporate them independently in the model. The model selects the theoretically optimal mix of land-use types by balancing the achievement of the four objectives when accounting for uncertainty (Romero, 2001). For further information about the robust optimization approach we refer the reader to the appendix for a formal model description and Knoke et al. (2020c). We used R (R Core Team, 2020) with the package optimLanduse (Husmann et al., 2021) to optimize our horticultural and forestry land-use portfolio.

2.3. Indicator settings and optimization scenarios

For our first research question we tested discount rates from 0 to 3% and conducted a sensitivity analysis to evaluate the robustness of our results to basic scenario assumptions. For instance, we assessed whether our results would be significantly altered either by extending the planning horizon from 46 to 52 or 64 years. For the forestry options, again two consecutive rotations of equal length are studied within the sensitivity analysis. Similarly, we evaluated whether changing assumptions about the lifespans of long-lived wood product pools significantly impacted our carbon sequestration results by considering product lifespans from 11 to 45 years, and also tested a scenario excluding these pools entirely.

We explore how discounting ecosystem services indicators might influence optimal land-use composition through optimization scenarios 1–4. While the optimization algorithm remains the same, we change the chosen social and ecological indicator sets for each scenario. The first two scenarios compare the effects of discounting non-market ecosystem services, and the last two scenarios consider the role of uncertainty. See Table 1 for the optimization scenarios.

Scenario 1 represents business as usual, where only socio-economic indicators are discounted. Scenario 2 discounts all cost and benefit indicators. Because the variability of ecosystem service growth rates across different service types and countries can be high (Baumgärtner et al., 2015), Scenario 3 uses three different discount rates simultaneously: we apply integer discount rates from 1 to 3% to ecological indicators, and from 2 to 4% for socio-economic indicators. Finally, Scenario 4 is explanatory and features smaller, because discounted, uncertainty spaces, but undiscounted ecological indicators. To illustrate the isolated impact of reduced uncertainties on the portfolio, starting indicator values are drawn from Scenario 1, but standard deviations are based on discounted options. Table A1 in the appendix specifies all indicator values for the respective ecosystem services.

2.4. Choice and estimation of the indicators

To capture the ecological and socio-economic performance of the six land-use types, we used four cost- and benefit- related indicators of ecosystem services based on MEA (2005) categories (Table 2). As socio-economic indicators, we chose (1) the net present value (NPV) and (2) the payback period (PP) to cover profitability and the sometimes problematic access to capital (Coomes et al., 2008). These socio-economic indicators reflect the market value of the ecosystem services of timber and fruit production, which cover financial benefits of the provisioning ecosystem services. They measure the financial efficiency of providing this service.

As indicators of ecological benefit and cost, we used (3) carbon sequestration (CS) in aboveground biomass and forestry product pools, and (4) fertilizer use (FU), respectively. We selected these objectives for the public planner's multiple, sometimes conflicting goals influencing land-use decision-making (Groot et al., 2018; Janssen and van Ittersum, 2007). While the socio-economic criteria reflected the benefits and costs measured as cash flows, the ecological indicators represented non-monetary benefits and costs. For the two ecological indicators we set the atmosphere as the reference frame. For the fertilizer indicator all yearly ecosystem service flows were emissions (=environmental costs), indicating the ongoing release of nitrogen. For the carbon indicator, we distinguished between carbon emissions (=environmental costs) and sequestration (=environmental benefits). In non-economic multi-objective studies, carbon storage is often measured as the average carbon stock over a longer interval, while a separate indicator for carbon sequestration might be used to capture periodic flows (see e.g. Peura et al., 2018). Our carbon storage indicator instead expresses net carbon flow (i.e. the sum of all discounted carbon sequestered and emitted) over the investment period. Thus, immediate emissions from harvesting are partly offset by carbon storage in wood product pools.

Table 1
Optimization scenarios and respectively considered indicators (using multiple discount rates means that all indicators are considered by their corresponding present values for this set of discount rates simultaneously).

Optimization scenario	Label	Discount rate for socio-economic indicators	Discount rate for ecological indicators
Scenario 1	Baseline	3%	0%
Scenario 2	Consistent discounting	3%	2%
Scenario 3	Discounting range	2, 3, 4%	1, 2, 3%
Scenario 4	Reduced uncertainty	3%	Non-discounted indicator values 0%, but discounted uncertainty values 3%

We simulated a baseline project period of 46 years, where the first establishment of every land-use type took place in year zero. Our project period covers two sequential forest rotations (23 years each) and one avocado rotation followed by an orchard clear-cut. Due to the different time horizons of avocado and forestry rotations, all indicator calculations referred to the project period and one representative hectare of the respective land-use type. We included benefit relevant indicators (NPV, CS) where a higher value is better, as well as cost relevant indicators (PP, FU) where lower values indicate a better performance. Below, we refer to this as the direction of the indicator.

Our study accounted for uncertainties in the provisioning of ecosystem services. Uncertainties included future market prices and production risks. Therefore, we used Monte-Carlo simulations for all uncertain indicators. The socio-economic indicators NPV and PP were subject to uncertain events for all land-use types. Fire risk was only considered for forestry options, since the risk of fire to avocado orchards is low due to extensive fire breaks and irrigation. Where uncertainty modelling was missing, like for the indicator fertilizer use, we assumed a volatility of 5% as variation coefficient and used the corresponding standard deviation. The financial data available in South African Rand (ZAR) (World Bank, 2021). Like other currencies, the South African Rand exchange rate is quite volatile in relation to multiple factors. Therefore, we accounted for fluctuations in the exchange rate when calculating the financial performance of the avocado export products. The Monte-Carlo simulations for the avocado therefore included bootstrapping of market price changes for domestic markets, as well as fluctuations in overseas costs and exchange rates for export markets (Roessiger et al., 2013).

2.4.1. Indicator 1: Net present value (NPV)

To calculate the NPV we discounted all cash flows during the investment period using a country-specific social discount rate, we varied from 2 to 4% (Addicott et al., 2020) and discrete time. The NPV implies that the land-use project considered is either marginal relative to the size of the other income sources of the decision maker or that a perfect capital market exists (Knoke et al., 2020a). Whereas we considered the outgoing cash flows like management costs as constant, incoming cash flows due to product sales were subject to fluctuations following Blandon (2004) and Paul et al. (2017). Company statistics and data from Crickmay and Associates (2019) provided timber price series and unpublished company statistics avocado prices (Jarisch, 2019). Expert opinions and long-term industry averages contributed estimates for the yearly harvest of avocado. An assortment allocation of 65% for export market, 15% for local market and 20% for further processing (avocado oil, guacamole) ranked best to lowest quality of fruits. Finally, common harvesting and management costs for all land-use types were based on expert interviews (Jarisch, 2019).

Furthermore, we included uncertainty components for each land-use type. We considered fire as the main production risk for the forestry plantations and assumed a failure probability of 1% per year. We added a 5% premium on harvesting costs and assumed that no pulpwood is available for sale after a fire. Due to the thinner bark of eucalyptus, we additionally reduced the share of merchantable eucalyptus sawlogs to 95% after a fire. For the avocado orchards, we included drought, hail, frost, extreme weather events, insect damage and sunburn in our uncertainty assessment. Fire breaks protect the horticultural orchards from burning. Other than for the forest stands, a failure event in the avocado orchards did not destroy the standing trees but reduced the crop yield. The calculation mechanism however was the same. With a mean risk

Table 2
Ecosystem services and their indicators for evaluating the performance of the land-use types.

Dimension	Ecosystem service	Indicator	Unit	Direction	Description
Socio-economic	Economic return from timber and fruit	Net present value (NPV)	US-Dollars per hectare	More is better	Sum of all discounted cash flows occurring during the investment period
Socio-economic	Regain of invested money from timber and fruit	Payback period (PP)	Years	Less is better	Time until the cumulative discounted net revenues cover the up-front costs
Ecological	Climate protection	Carbon sequestration (CS)	Megagram Carbon per hectare	More is better	Sum of all carbon storage changes during the investment period
Ecological	Environment and climate protection	Fertilizer use (FU)	Kilogram Nitrogen per hectare	Less is better	Sum of all fertilizer output changes during investment period

probability of 20% per year, we considered 80% of the regular yields and a changed assortment allocation to 50% export market, 20% local market and 30% factory components. For the NPV we assumed "more is better" as indicator direction.

2.4.2. Indicator 2: Payback period (PP)

As access to money is limited for most persons and companies, the time until the invested money is received back is a useful indicator to consider economic preferences (Peterson and Fabozzi, 2002). The payback period relates to the objective of maintaining timely cash flows and accounts for access to money (liquidity). This indicator is important, if the investor depends on the project, with only limited financial alternatives. In an empirical context where capital market imperfections must be considered, the payback period accounts for the often-limited access to capital. We calculated the payback period for all our land-use types based on a social discount rate ranging from 2 to 4% (Addicott et al., 2020). The time until the cumulative discounted net revenues cover the up-front costs defines the payback period (Peterson and Fabozzi, 2002). We therefore compared initial investment and the risk-dependent discounted returns to calculate the year of amortization. Based on the Monte-Carlo simulations for the NPV calculation, we included risk assessment and price fluctuations within the calculation of the payback period. We assumed decision-makers prefer smaller payback periods and set the indicator direction accordingly.

2.4.3. Indicator 3: Carbon sequestration (CS)

Carbon sequestration as an environmental benefit indicator reflected the contribution of the land-use types to climate protection. We set the indicator assessment similar to Assmuth et al. (2021) and focused on the discounted sum of net yearly changes in carbon sequestration, rather than the absolute storage numbers. Unlike Assmuth et al. (2021) we discount indicator flows directly, instead of considering monetary values of periodic carbon flows for the subsequent optimization. We follow the idea of discounting carbon sequestration, but apply the discounting principle consistently to all biophysical indicators for environmental benefits and costs and to both their expected and worst-case values. Thus, the influence of discounting under uncertainty is a central point in our study, which is rarely addressed in other studies.

We modelled the sum of age-dependent carbon uptake and emission rates based on storage in the aboveground biomass for all land-use types. Unlike Assmuth et al. (2021) we excluded deadwood as carbon storage, as South African plantation standards neglect deadwood due to the increased fire risk associated with a higher fuel load. Instead, for the forestry options we added the storage of long-lived products made from harvested wood during the investment period. To account for the time-dependent occurrence of carbon uptake, we calculated yearly changes in the carbon storage pools and summed them over the investment period, discounting each to the present moment. We compared discounting results of the physical carbon storage for an ecological discount rate ranging from 0 to 3%.

For the avocado options, we calculated the standing tree biomass at the end of the rotation following the equations of Chave et al. (2005) for moist forest types. In order to calculate standing biomass and carbon sequestered for a representative hectare, we obtained information about tree height, diameter, and tree numbers per hectare from expert interviews and industry data. We accounted for 50% of the dry wood mass as stored carbon fraction (Matthews, 1993). We calculated a carbon sequestration rate of 0.37 Mg C $ha^{-1}y^{-1}$. At the end of the avocado rotation, all biomass is used as fuel wood or burned on site, leading to a total release of all sequestered carbon for both horticultural options. For the avocado orchards, no calculation of a standard deviation based on Monte-Carlo simulations was possible, as the risk assessment covered fruit production only and not the failure of standing trees as above-ground biomass. Therefore, we assumed a volatility of 5% for avocado data for carbon sequestration instead.

For the forestry land-use types, we used growth and grading data (Microforest Limited, 2019) in combination with tree component biomass factors by Dovey (2009) to calculate the yearly carbon sequestration rates. As with the avocado trees, we accounted for 50% of the dry wood mass as stored carbon fraction (Matthews, 1993) and calculated age-specific carbon sequestration rates for each forest stand. Over the project horizon, the mean carbon sequestration rates for the forestry plantations ranged from 3.56 Mg C $ha^{-1}y^{-1}$ for *P. elliottii* to 5.60 Mg C $ha^{-1}y^{-1}$ for the eucalyptus clone (see Table A2 in the appendix). Furthermore, we calculated carbon stored in wood products pools for differing lifespans. For harvesting as well as thinning operations, we calculated product pools for 80% of the saw log assortments. No storage, but direct release, was assumed for pulpwood and the remaining 20% of saw log grades. Analogous to the economic calculations, we reduced the amount of saw timber available for product pools after a fire. The plantation age was set to zero after simulation of a fire and the carbon uptake followed the age-dependent sequestration rate. The direction set for this indicator favored higher values of carbon sequestration, because this mitigated the emissions of greenhouse gases.

2.4.4. Indicator 4: Fertilizer use (FU)

Mineral fertilizers are mainly based on nitrogen and entail costs related to greenhouse gas emissions, as well as to negative impacts on groundwater quality, health and biodiversity (Basosi et al., 2014; Keeler et al., 2016; Maghanga et al., 2013; Townsend et al., 2010; Zebarth et al., 2009). For mitigating climate change and costs of health, reduced fertilizer use is considered favorable, which led to the direction of this indicator as "less is better".

We calculated the fertilizer use for every land-use type based on data from Lewis et al. (2019) and company-specific management recommendations. No fertilizer was used in the silvicultural regime for pine stands. Both eucalyptus stands were fertilized only at establishment with 39.8 Kg N ha^{-1}. Yearly fertilization took place in the avocado orchards with 195.0 Kg N $ha^{-1}y^{-1}$ (Lewis et al., 2019). For the indicator, we summed up the yearly amount of fertilizer use within an investment period. To discount the indicator we used an ecological discount rate ranging from 0 to 3%. For the standard deviation, we assumed a fluctuation of 5% for all land-use types as uncertainty models were missing.

2.5. Selected land-use types

Our study covers six different land-use types, presented in Table 3. We simulated the forest stands with the growth and yield modelling tool of the Microforest plantation management system (Microforest Limited, 2019). The forest stands were even-aged monocultures of either *Pinus patula, Pinus elliottii, Eucalyptus grandis* or the clone *E. grandis x urophylla*. Based on South African growth data, we modelled pruning and thinning over the 23-year rotations for each species (Microforest Limited, 2019). Pine and eucalyptus stands produced mainly saw wood, following a company-specific silvicultural regime. Pulpwood, poles, mining timber and other assortments are by-products sold after thinning or harvesting operations. We set site- and age-specific grading tables for all forestry stands related to industry norms (Jarisch, 2019).

As horticultural options, we defined an irrigated and a dryland avocado orchard with the common, black-skinned cultivar 'Hass'. Both horticultural options are managed within a 46-year period, while starting to produce fruit at the age of two. Besides picking, regular orchard management like fertilization, phytophthora control, and weed control take place every year. As is typical for avocado, we considered on and off years of fruit production with yields alternating between 15 and 18 tons per hectare for mature stands. Dryland management saves the costs for establishment and maintenance of irrigation systems but obtains lower yields. In our study, we assumed 80% of the regular yield for the dryland orchards (Jarisch, 2019).

The economically optimal rotation for each land-use type depends, inter alia, on the discount rate. However, we use pre-defined rotation lengths for our land-use type options, which are selected according to common South African plantation management practices.

2.6. Using the Shannon index as diversity measure

To measure the diversity of the land-use portfolios we calculated Shannon's diversity index (H) (Nagendra, 2002), which measures the number of different categories in a dataset and their relative abundance. Whereas most studies use Shannon's H in an ecological context to display species richness, we measure the number of different land-use types per portfolio composition, following Friedrich et al. (2021) and Ochoa et al. (2019). Further examples who study diversification in an economic context based on the Shannon index are Adeola and Evans (2017) and Pede (2013). The diversity of a landscape composition is higher the more land-use types are integrated and the more even their distribution. We calculated the dimensionless Shannon index from the decimal shares of the land-use types. If all possible land-use types are equally incorporated in the portfolio we obtain the maximal possible Shannon index. In our case the six options result in a maximal possible Shannon index of 1.79. We compare the intensity of land-use type diversification for our farm portfolios based on this diversification measure.

Table 3
Characterization of the simulated land-use types (one project period covers two consecutive forestry rotations).

Land-use type	Abbreviation	Description
Pinus patula	Ppat	Monoculture of *P. patula* with the aim to produce saw wood within 23 years of rotation time Interventions: Pruning (x4), thinning (x1)
Pinus elliottii	Pell	Monoculture of *P. elliottii* with the aim to produce saw wood within 23 years of rotation time Interventions: Pruning (x3), thinning (x1)
Eucalyptus grandis	Egra	Monoculture of *E. grandis* with the aim to produce saw wood within 23 years of rotation time Interventions: Pruning (x4), thinning (x3)
E. grandis x urophylla	Egxu	Monoculture of *E. grandis x urophylla* with the aim to produce saw wood within 23 years of rotation time Interventions: Pruning (x4), thinning (x3)
Persea americana Cultivar 'Hass' Irrigated orchard	Avo	Irrigated orchard of the avocado cultivar 'Hass' with the aim to produce fruit. Clearcutting the orchard in year 46. Yearly picking starts at age 2, stands reach maturity at age 7
P. americana Cultivar 'Hass' Dryland orchard	AvoDry	Dryland orchard of the avocado cultivar 'Hass' with the aim to produce fruit. Clearcutting the orchard in year 46. Yearly picking starts at age 2, stands reach maturity at age 7

3. Results

3.1. Discounting of ecosystem services

Discounting the non-market ecological indicators (CS, FU) changed their provisioning in two ways. While we observed a consistent decline for the standard deviation of both indicators, the development of the indicator values itself varied with increasing discount rates (Fig. 2, Table A3, Table A4 in the Appendix).

We present the discounted carbon sequestration in Fig. 2 for our baseline and sensitivity analysis. As we defined temporary carbon storage as the sum of (discounted) sequestration and release, clearcutting avocado orchards at the end of each rotation releases all carbon sequestered as aboveground biomass into the atmosphere (since product pools do not exist for these wood residues being burnt on site), resetting carbon storage to zero in the non-discounted scenario (Table A3). However, with increasing discount rates the discounted carbon sequestration of the horticultural options increased till a discount-dependent peak, beyond which the development leveled off (Fig. 2, Table A3). Discounting reduced both the benefit of late carbon storage and the cost of end-of-rotation carbon release. The peak indicates the discount rate resulting in the greatest discounted carbon benefits.

In our study forest land-use types provide carbon benefits also when assuming a discount rate of zero due to fire risk modelling and product pools. If a fire occurs within the investment period, the final harvest is postponed beyond our planning horizon, although the effect is marginal because forestry carbon flows are dominated by wood product pools. If we would have used a longer time horizon, this carbon would still be released to the atmosphere sometime under the carbon flow approach. As a result, the fire-affected proportion of the 5000 Monte-Carlo simulations provide a carbon storage of standing biomass lasting longer than the investment period, which leads to carbon benefits even for a 0% discount rate. The higher growth rates of eucalyptus species lead to higher biomass accumulation, which is reflected in higher carbon sequestration rates in comparison to the pine species.

For studying the impact of product pools, we exemplarily present *P. patula* as land-use option. Adding and increasing the lifetime of product pools enhanced the carbon storage (Fig. 2 -Panel B). With increasing discount rates, we observed a consistent decline in the carbon indicator for forestry scenarios with product pools. Forestry scenarios without product pools showed a slight increase till a discount-specific peak and then leveled off. Carbon storage for long product lifespans was best for a discount rate equal to zero, whereas assuming no product pools showed highest benefits for scenario-specific discount rates (Table A3). Panel B illustrates the high impact of product pool assumptions on the overall indicator performance for forestry options. As discount rates shrink, the share of carbon stored in wood product pools dominates, making moderately-discounted scenarios especially sensitive to product longevity assumptions (Fig. 2).

Variations of the project horizon are displayed in Fig. 2 –Panel C. Enlarging the project period leads to increasing carbon sequestration. Avocado cultures with longer rotation times reached the peak of carbon sequestration at a lower discount rate.

Discounting did not affect the fertilizer use indicator for forestry options, since fertilizer was either not used or applied only once in the year of stand establishment (Table A4). For the avocado options, we observed a decline of the ecological costs of fertilization for increasing discount rates for all rotation times.

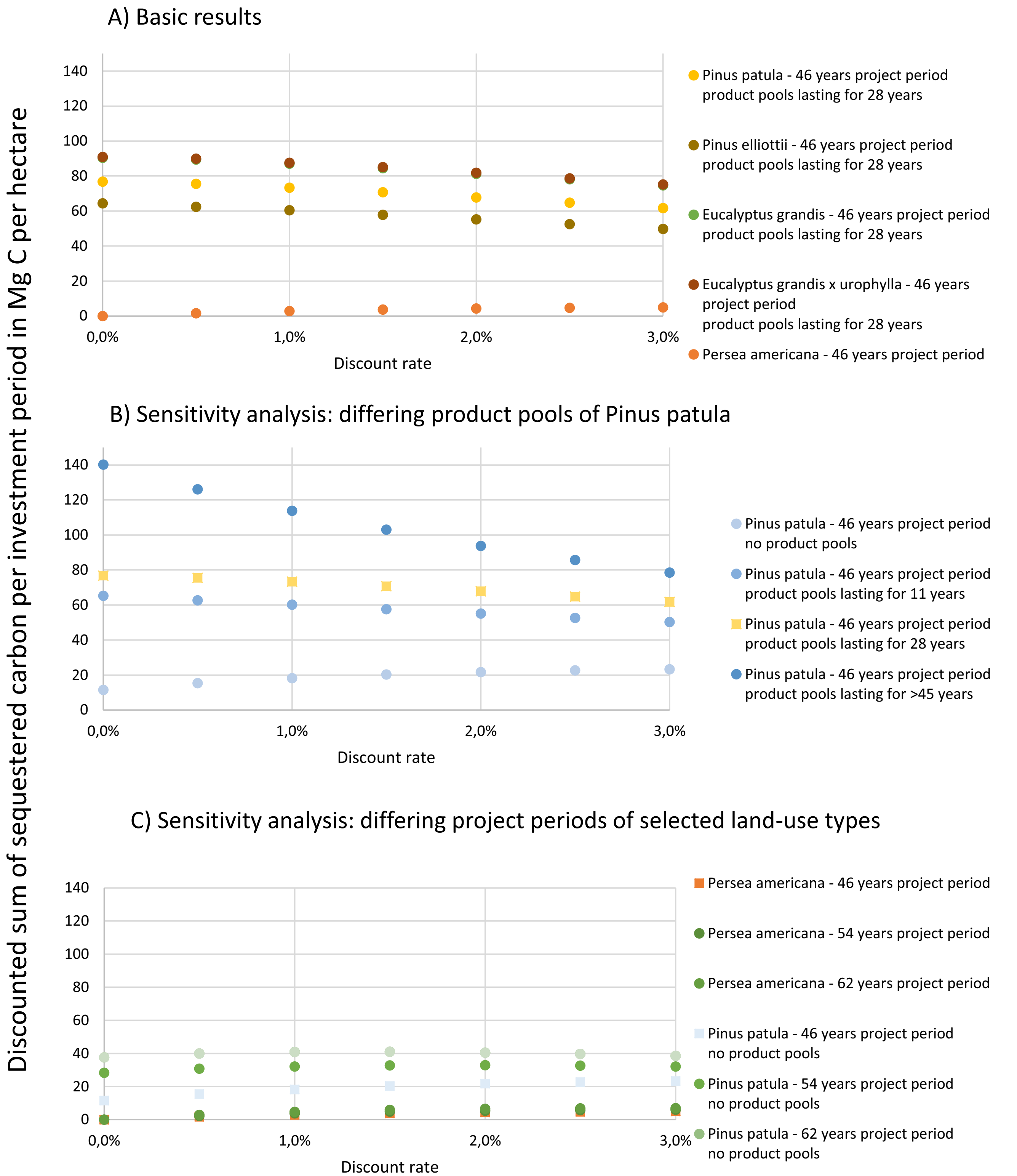

Fig. 2. Ecological indicator: Discounted sum of carbon sequestration in Mg C per hectare (for the forestry options the project period is divided into two consecutive rotations with equal length; Irrigated and dryland avocado option show the same indicator performance and are therefore not distinguished).

For all ecological indicators and land-use types, differences between scenarios decreased with increasing discount rates (Table A3, Table A4, Fig. 2). The longer the investment period (or the greater the discount rate), the smaller the impact of late costs or benefits. Indicator provisioning between the project period scenarios for the land-use types varied the most with smaller discount rates; higher discount rates produce smaller standard deviations (Table A3, Table A4, Fig. 2, Fig. 3) for all indicators and land-use types.

3.2. *Robust multi-objective optimized land-use portfolios*

To illustrate the impact of discounting ecosystem services on optimal

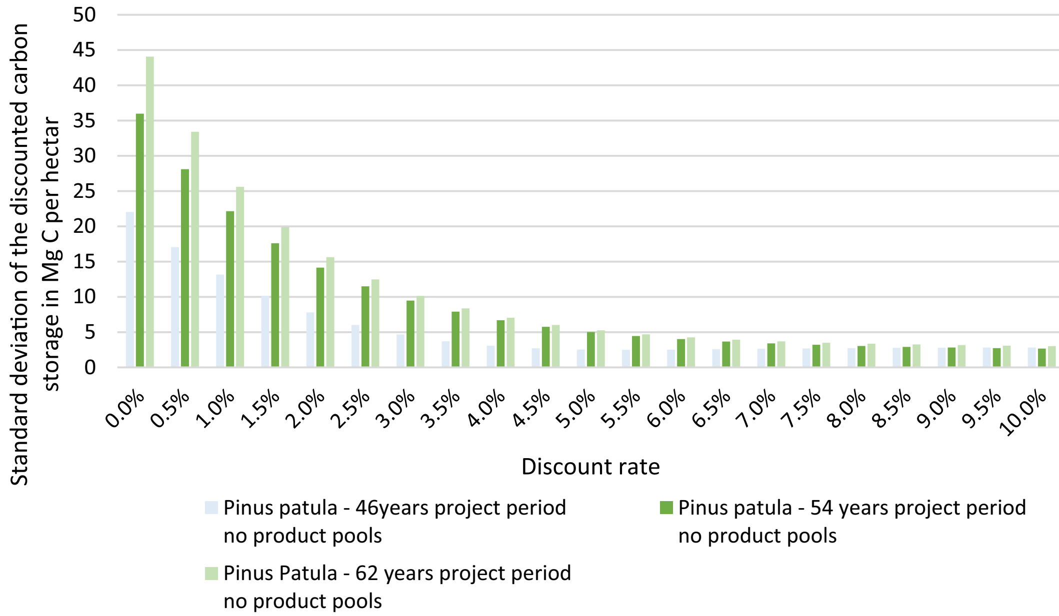

Fig. 3. Standard deviation of carbon sequestration over the discount rate for selected project periods of *Pinus patula*.

land allocation, we present scenarios 1–4 in Fig. 4. We modelled the land-use portfolios for uncertainty factors ranging from 0 to 3.5, representing increasing uncertainty aversion from left to right within each of the four scenarios.

3.2.1. Baseline scenario

In the baseline scenario, an uncertainty-tolerant decider (leftmost bar) would choose a portfolio consisting of 57% *E. grandis* and 43% irrigated avocado. While the irrigated avocado performed worst for the ecological indicators, it showed by far the highest financial return. However, yield and exchange rate fluctuations were high, making the irrigated avocado a risky land-use option. With increasing uncertainty, the model incorporates more land-use types. The high growth rate of eucalyptus lead to good financial performance, as well as high carbon sequestration. In comparison with the other land-use types, the uncertainty profile of both eucalypt species represented moderate risks, which explains their inclusion in the optimal land-use portfolios across nearly all uncertainty levels. For a moderate level of uncertainty ($m = 1.5$), the farm portfolio consists of four land-use types: namely, the irrigated avocado orchard, both eucalyptus species, and *Pinus patula.* For increasing

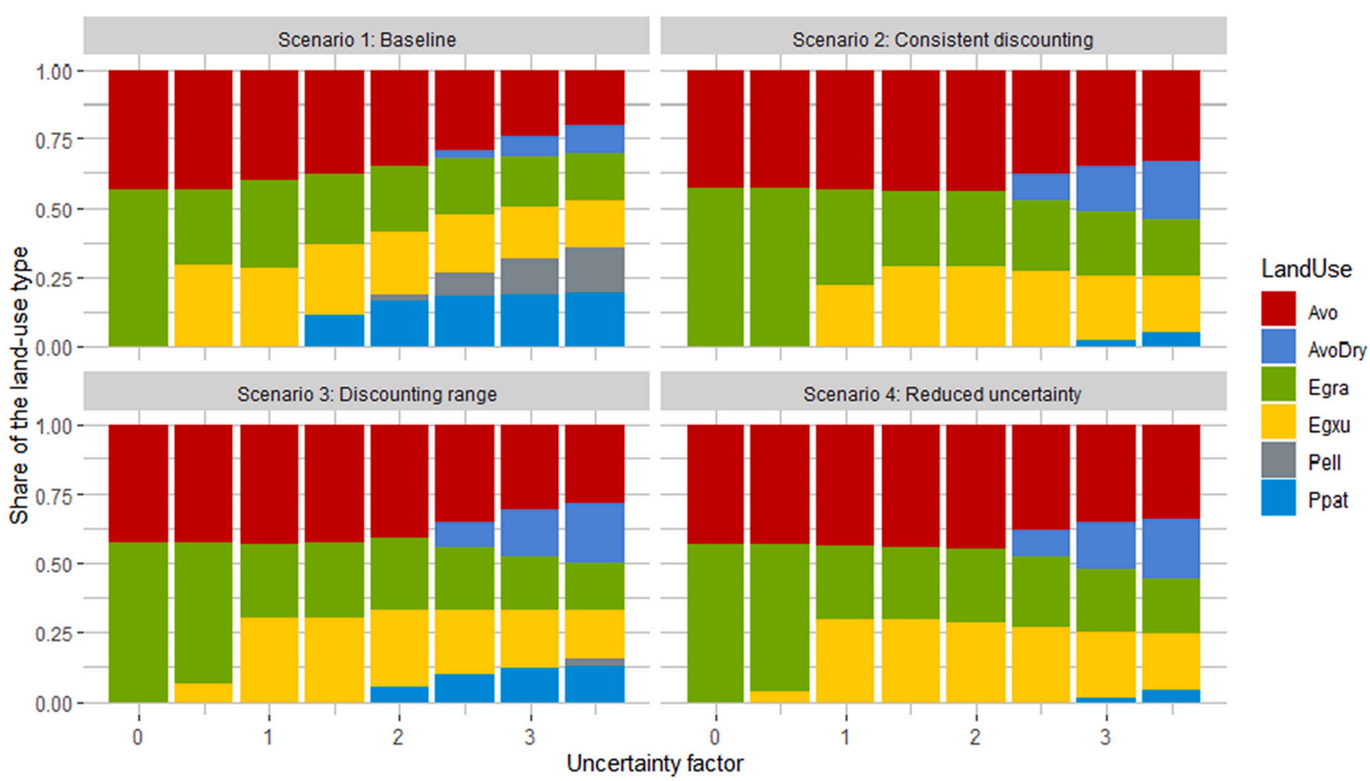

Fig. 4. Land- use portfolios for the four optimization scenarios, uncertainty aversion increasing from 0 (left) to 3.5 (right) within each scenario.

uncertainty, the algorithm adds stepwise *Pinus elliottii* and the dryland avocado option. Both pine species performed well on the ecological indicators, but *P. elliottii* had a very low financial performance. In the baseline scenario, a strongly uncertainty-averse decider (rightmost bar) would choose a portfolio composed of all six land-use types with a relatively balanced composition. The optimal land-use composition for achieving the four objectives best highly depends on the decision-maker's attitude toward uncertainty.

3.2.2. Influence of consistent discounting

Using ecological and social discount rates consistently for all costs and benefits reduced portfolio diversification. As in the baseline scenario, the algorithm incorporated more land-use types for higher uncertainty factors, but the maximal number of considered land-use types is smaller. For the highest uncertainty factor, the portfolio included just four land-use options. Moderate uncertainty aversion led to portfolios dominated by avocado and *E. grandis* with contribution of the eucalyptus clone; dryland avocado was included for strong uncertainty aversion. The share of avocado (both options combined) grew with increasing uncertainty aversion, in contrast to the baseline scenario where the combined share of avocado decreased with increasing uncertainty aversion.

3.2.3. Influence of a discounting range

When accounting for the uncertainty of the discount rate, the effect of reduced diversification is moderated or almost offset in comparison to Scenario 2. The discounting range portfolio shows only slightly less diversified portfolios than the baseline scenario, but higher diversification than consistent discounting with just one rate. For the highest level of uncertainty all six land-use types are included ($m = 3.5$). Like all scenarios, the uncertainty-neutral decider would choose a portfolio consisting of *E. grandis* and irrigated avocado. In comparison to scenario 2, the number of included land-use types is higher for the discounting range for the respective uncertainty aversion and the composition is more balanced. While the eucalyptus proportion varied, the avocado share was nearly the same between scenarios 2 and 3. For higher uncertainty aversion, the model included *P. patula* and for highest uncertainty aversion even *P. elliottii*. However, in comparison to the baseline scenario, the pine species are missing for low to moderate uncertainty aversion. Again, like Scenario 2, the combined avocado share grew with increasing uncertainty aversion for the discounting range scenario and the share of avocado without irrigation increased when considering high levels of uncertainty.

3.2.4. Influence of reduced uncertainty

Considering only discounting-reduced standard deviation, but no discounting of the indicator values as such, explains already most of the changes in the portfolio composition resulting from discounting. Scenarios 2 and 4 differ just in the proportional distribution, except for $m = 0.5$ the incorporated land-use options are the same. In comparison to the baseline scenario, the reduced uncertainty of discounted indicator values led already to less diversified portfolios. Even for high uncertainty aversion, just five land-use types were selected. *P. patula* was only included in portfolios for high uncertainty factors. Reducing the uncertainty of discounted indicators yielded less diversified portfolios.

3.2.5. Shannon index

The Shannon indices for all scenarios increased with higher uncertainty factors (Fig. 5), indicating higher diversification for increased uncertainty aversion. While the baseline scenario showed the highest index values among all scenarios, the other scenarios led to less diversified portfolios. The consideration of a set of discount rates (scenario 3: Discounting range) resulted in Shannon indices slightly higher than scenario 2 with consistently discounted indicators.

4. Discussion

There is a large, and largely unexamined, discrepancy in how the ecosystem services literature treats monetary and non-monetary flows that occur in the future: the former are almost always discounted, the latter just rarely. This discrepancy impacts the relative weight that these types of flows receive in multi-criteria decision settings (Kula and Evans, 2011). In the case of non-monetary costs and benefits, consistently ignoring time preference and risk might produce land-use allocations

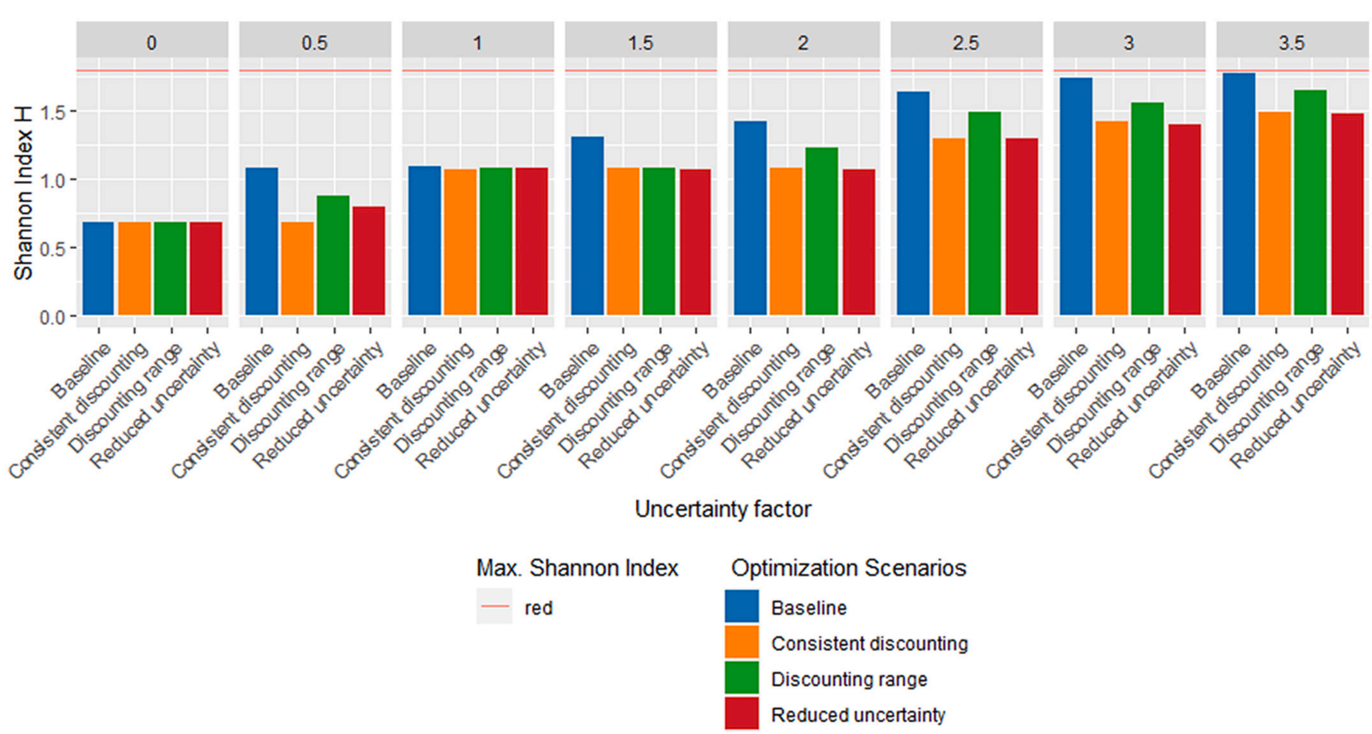

Fig. 5. Shannon Indices for the four optimization scenarios and increasing uncertainty factors.

that fall short of the social optimum.

We present the first analysis of the effect of discounting ecosystem services production on multi-objective land-use allocations under uncertainty and describe a method for accounting for uncertainty in the discount factor. Our study is based on a virtual farm portfolio concept in which shares of future land-use types are allocated within different discounting and uncertainty scenarios. In our forestry-avocado example, the baseline scenario with only monetary flows discounted produced the most diversified and balanced land-use portfolios. Applying ecological discount rates shifted the value of both ecological indicators in a direction that favored avocado over forestry: it made both the total fertilizer use (a cost associated with avocado) and the carbon stored at the end of the planning horizon (a benefit associated with forestry) appear smaller. Thus, the area share allocated to avocado agriculture increased when ecological discount rates were included.

To center the relationship between discounting and multi-objective allocation decisions, we used a simplified bare-land model that neglects conversion costs. If establishing an avocado orchard or forest plantation required clearing existing bush- or woodland, then that would entail an initial, and thus undiscounted, carbon release, which could have a large effect on optimization results. In KwaZulu-Natal, carbon loss is calculated at a rate of 0.54% per annum, underscoring the importance of strategies that retain and enhance landscape carbon storage (Turpie et al., 2021). In practice, large scale timber growers typically manage age-balanced plantations, where an equilibrium of carbon uptake and release is expected over the long term under current conditions.

Assumptions about the size and durability of carbon pools had substantial effects on optimal land-use portfolios, especially when discount rates were small. We modelled carbon sequestration in aboveground biomass, which we fractionated post-harvest into wood product pools with different lifetimes. We only accounted for direct sequestration and ignored material substitution effects, so our approach likely underestimates the carbon sequestration potential of the forestry options (see e.g. Härtl et al., 2017). For orchards, we neglected the carbon effects of pruning and the fate of pruned branches (e.g. mulching). Importantly, we did not account for fossil fuel emissions from machinery used in management or harvesting activities. As we defined our carbon indicator as net sum of carbon sequestration and release, without any changes of the average carbon stored in situ or in various carbon pools, we need to discount carbon flows to show the beneficial effect of "buying time" by first sequestering and later releasing the carbon again into the atmosphere. For the forest land-uses even non-discounted carbon benefits occur due to fire risk and product pools; this carbon would have been released to the atmosphere if we would have enlarged the project period till the end of the product lifetime. For our optimization scenarios we considered only forestry options with moderate product lifetimes, where we argue that the added storage due to our fire modelling approach is negligible as it's the minor share.

Discounting carbon sequestration directly is less common in practice than one might expect. Early work discounted the monetary value of periodic carbon flows, i.e. the product of sequestration units with a carbon price (Plantinga and Birdsey, 1994; van Kooten et al., 1995). Although recent studies report values that are equivalent to discounted physical carbon flows (Assmuth et al., 2021, 2018; Pihlainen et al., 2014), these values are not used as decision variables; monetary values are used instead for management advice. Our study instead optimizes based on directly discounted physical carbon flows, thereby demonstrating a method for integrating time preferences into decision-making that avoids strong assumptions about the economic value of ecosystem services in the absence of reliable price data (e.g. due to missing or volatile markets). Without discounting, the value of forest-based carbon sequestration is determined by age-dependent uptake rates (Akao, 2011), but discounting progressively de-prioritizes long-term storage (Yousefpour et al., 2018). In our study, the benefits of binding carbon in wood products taper off with higher discount rates. This implies that excessive carbon discounting could undercut climate-oriented efforts to promote the adoption of long-lived timber products, because these product pools often require larger wood dimensions and longer rotation periods. Where social discount rates are low, as in Europe, dual discounting might not be needed to support postponed-release tactics over alternative uses. Increasing carbon discount rates—which might be done to address criticisms that forest-based sequestration projects overstate their permanence and fail to address the risk of large disturbance-induced mortality, for instance (Gren and Aklilu, 2016)—favors shorter-term sequestration strategies.

Our virtual farm portfolio approach engages with uncertainty at two levels: discounting and optimization. The optimization model uses diversification to hedge against uncertainty (Knoke et al., 2020c; Reith et al., 2020; West et al., 2021), whereas discounting is an a priori approach that accounts for uncertainty by reducing the future costs and benefits our model evaluates. These tools can counterbalance one another. Within each scenario, diversification was positively associated with increasing uncertainty as the model attempted to hedge against high indicator variance. Between scenarios, however, those featuring heavy discounting generated less diversified portfolios than those featuring light discounting. This is because discounting limits the impact of late-occurring uncertain events on present values. As a result, indicator variance is constrained, less hedging is required at the optimization stage, and more area is allocated to the best-performing land uses - in this case, avocado orchards. Our study showed that applying discount rates to all ecosystem services would tend to reduce the compositional diversity of the land portfolios. However, this tendency of homogenization to gain more efficiency did ignore the uncertainty of the discount rate itself. It appears to be essential to consider this discount rate uncertainty to obtain balanced results and to apply discounting of all ecosystem services with due care.

Although we do not explicitly weight our objectives, beyond the implicit weighting derived from varying discount rates, assigning weights in our optimization model is mathematically possible. Including indicator weights is unlikely to substantially alter the positive association between uncertainty and diversification. Robust optimization uses a min-max decision rule that allocates area shares to obtain the best result from the worst-performing indicator, so that strong performance in one dimension cannot compensate for weak performance in another. Heavily weighting one objective could allow it to dominate the results by favoring the best-performing land-use type, but diversification would still increase with increasing uncertainty. Our method is relatively robust against implicit weighting effects by different numbers of indicators which represent the objectives for land allocation. As the maximum distance of an indicator to the best achievable level (ideal point) is minimized, the outcome does not depend directly on the number of indicators, but on which of the indicator is worst performing.

For practical purposes, however, how to weight indicators expressing different kinds of values remains an open question. In economics, this issue is typically avoided by commensuration through the money metric or by the use of utility, whereby wants and needs are expressed as undifferentiated and grossly substitutable magnitudes (Gomez-Baggethun and Martin-Lopez, 2015; Kant, 2003; Spash and Hache, 2021). In ecosystem services, debates about how best to weight differentiated and largely un-substitutable objectives remain unresolved, and range from bureaucratic additive metrics like the Environmental Benefit Index of the US Conservation Reserve Program (Everard, 2018; USDA, 2021), to Pareto frontier methods that attempt to offload the weighting problem to stakeholders (Marques et al., 2020), to soliciting weights using various expert consultation frameworks (Fanghua and Guanchun, 2010; Marto et al., 2018; Vacik et al., 2007). In this study, we consider severe uncertainty where decision-makers can identify different scenarios but cannot rank the likelihood that they will be preferred by the next generation of decision-makers (Friedrich et al., 2021; Kwakkel et al., n.d.), so we omit objective weights.

Using a money metric may clarify how trade-offs are made between objectives, but the issue of intertemporal trade-offs remains elusive. Selecting an appropriate discount rate can be extremely challenging even in the familiar context of cash flows, partly because it often requires making assumptions about consumption growth. Indeed, it is sometimes argued that the most significant source of uncertainty in cost-benefit analysis is the discount rate itself (Weitzman, 2001). This challenge is compounded in the case of ecosystem services, where relevant considerations expand to encompass other fluctuating and difficult-to-predict factors like intergenerational equity, substitutability with consumption goods, and the scale of expected erosion of ecosystem services (Baumgärtner et al., 2015; Drupp, 2018; Nichols et al., 2011; Zhu et al., 2019). Ecosystem services production functions are subject not only to high standard errors linked to service types and national contexts (Baumgärtner et al., 2015), but also to disturbance risk, which influences Ramsey discount rates (Rennert et al., 2021). Finally, discount rate selection has important ethical implications that might be overlooked by strictly financial calculations (O'Mahony, 2021; Sjølie et al., 2013). Unlike a private person preferring a good now rather than later, a public planner considering social discounting accounts for intergenerational welfare (Kumar, 2010). Future research might seek to develop alternative approaches for engaging with discount rate uncertainty. For the time being, it is advisable to consider a range of possible discount rates (Hoel and Sterner, 2007).

Different discount rates can also be used for different kinds of values. Contrary to the standard practice of using a single, fixed discount rate for costs and benefits, Medvecky (2012) points out that differential rates might be desirable in some cases, such as a uncertainty-averse decision-maker who weights future costs more heavily than future benefits. Similarly, with decreasing ecosystem service provisioning (IPBES, 2019; MEA, 2005), using a special ecological discount rate can help account for declining natural capital, even when social discount rates reflect expectations of continued economic growth. Kula and Evans (2011) find that including an extra ecological discount rate and implementing dual discounting could increase the economic viability of investments designed to generate environmental benefits. Here, we use the same rate for costs and benefits, but different rates for socio-economic and ecological indicators.

Due to the long-term nature of most environmental assessments, the use of static discount rates for ecological indicators has become somewhat controversial (Gollier, 2010; Groom et al., 2005; Knoke et al., 2017; Kula and Evans, 2011; O'Mahony, 2021; Rennert et al., 2021; Weitzman, 2001). Although we opted for static discount rates, there is a growing literature on discount rates that change over time according to a schedule as a strategy for balancing uncertainty and sustainability. Limited substitutability and increasing uncertainty about growth, risk, and market conditions might support the adoption of non-constant discount rates (Traeger, 2011; Zhu et al., 2019). For instance, carbon sequestration in forests is a product of biophysical processes influenced by stochastic environmental conditions and evolving disturbance regimes (Seidl et al., 2014), so the permanence in forest carbon sequestration is highly questionable (Gren and Aklilu, 2016). Reed (1984) famously demonstrated that a policy effect related to a fire risk assessment is linked to adding a premium to the discount rate that would have been used in a risk-free environment. Also Malo et al. (2021) show that the optimal forest management strategy is in the same manner influenced by a higher discount rate as by accounting for hazard events. Following Gollier (2014) a risk premium could therefore even lead to an increasing term structure of the discount rate.

Of course, the more common approach to non-constant discounting for long-term assessments is to use declining discount rates, which are often observed (Newell and Pizer, 2003) or recommended (Arrow et al., 2013). However, setting the appropriate term structure under declining discount rates may be a challenge (Freeman and Groom, 2016). It also greatly complicates the optimization of forest management (Knoke et al., 2017).

For some ecosystem services (e.g. water supply) substitution possibilities are limited (Fitter, 2013), leading to higher relative prices (Drupp, 2018). For long-term assessments, even a non-constant elasticity of substitution between ecosystem services and manufactured goods seems plausible due to subsistence requirements as the elasticity varies with the availability of the service (Drupp, 2018). Low substitutability possibilities and high prices for ecosystem services lead to ecological discount rates that are significantly smaller than for manufactured goods. The less man-made inventions can substitute for ecosystem services, the more appropriate a declining discount rate becomes (Zhu et al., 2019). It should be noted that while weak sustainability allows this kind of substitution, strong sustainability does not, and requires financial and ecological consumption to be addressed independently.

As a final point, standard economic assessments arguably meet their limits in decision environments involving irreversible damages to rare ecosystems and the loss of the services they provide (Kumar, 2010). Discounting alone cannot address, and in some cases may exacerbate, unsustainable decision-making. When and how discounting should be applied in the ecosystem services context is far from self-evident. Further work on this important topic—up to and including vigorous debates—should be encouraged.

5. Conclusions

Our study presents how robust, multi-objective land-use portfolios change when considering time-preferences for ecosystem services in a mixed forestry-avocado farm portfolio in South Africa. This was examined by consistently discounting ecosystem service indicators with specific discount rates in multi-objective optimization. Our result indicate that multi-objective optimization is a valuable tool for public planners to fulfill famers' and policy makers' interests in modern land management. As discounting shifted the ecological indicators of avocado orchards in the desirable direction, dual discounting increased the shares of avocado farming over the forestry options. Discounting favors near-term streams of benefits over postponed returns, which influenced the indicators based on the assessment framework as shown in our sensitivity analysis. Dual discounting moreover accounts separately for time preferences of ecological costs and benefits. Discounting decreased the standard deviation of the ecosystem service indicators which led to reduced portfolio diversification. Considering time preferences consistently led to highly efficient-orientated land-use portfolios. However, for ecosystem services with high scarcity and low substitution possibilities, low ecological discount rates are recommended which encourages portfolio diversification. Cost-benefit analysis of land-use management problems could move to a dual focus on both efficiency and sustainability when discounting ecosystem service indicators separately with adapted rates. However, as discounting focuses on near-term effects, it discriminates against late ecosystem services flows. For services like nature conservation or water regulation, choosing the right discount rate is therefore especially important. Nonetheless declining provisioning of ecosystem services and questionable substitution possibilities of ecosystem services suggest dual discounting when considering ecological costs and benefits in decision-making. For future studies on land-use management declining discount rates or hyperbolic discounting could be a promising option to meet sustainability and intergenerational equity in land-use decision-making. To capture ecological and social effects in a more comprehensive approach, life cycle assessments could be a valuable tool for future indicator assessments.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Appendix A. Appendix

A.1. Robust multi-objective optimization approach

Our robust, multi-objective optimization approach seeks to allocate land-use shares in a way that minimizes trade-offs between the ecosystem service indicators. We consider our model as robust, because it guarantees satisfactory solutions across a wide range of input data (Ben-Tal et al., 2009). When setting up the decision environment, the model not only accounts for the predicted performance of each land-use type for achieving each ecosystem service indicator, but also potential fluctuations in this performance. The optimization algorithm compares the distance between the indicator levels achieved by a given farm portfolio and a reference point under uncertainty. We define discrete uncertainty scenarios u, based on all systematical combinations of the best and worst cases for each indicator and each land-use type (Gorissen et al., 2015). This results in 2^L scenarios per indicator, with L being the number of land-use types considered in the optimization.

These uncertainty scenarios u, which form the surface of the box-shaped uncertainty spaces, U_i for each indicator i, represent our missing knowledge about future developments. Such future developments could include, for example, significant changes in environmental and market conditions over time. We limited our consideration of uncertainty to the negative side of the results, because we see risk as an asymmetric phenomenon, where positive deviations are opportunities that can be ignored in risk modelling (Račev et al., 2008). The best and worst case values for each land-use type form the corner points of the uncertainty space for each indicator. The optimization then considers all corner points simultaneously. Therefore the optimal land-use portfolio offers a feasible solution for all input values contained within the uncertainty spaces (Knoke et al., 2020c).

The most desirable level for each indicator of each single land-use type is set as the reference point in our study (Diaz-Balteiro et al., 2018; Estrella et al., 2014). This ideal indicator level cannot be achieved for all ecosystem services and all uncertainty scenarios simultaneously. Instead, the optimization algorithm minimizes the maximum distance β between the actual performance level and the reference point across all indicators and uncertainty scenarios (Knoke et al., 2020c). The solution forms the best compromise across all uncertainty scenarios by presenting the most desirable portfolio composition, where high levels of one indicator do not compensate for low levels of another (Romero, 2001).

The predicted values $\widehat{y}_{i,l}$ for each ecosystem service indicator, i, and land-use type, l, form the starting point for the robust optimization model. To account for the indicator fluctuations we compute the uncertainty adjusted values $y_{i,l,u}$ that span from the best- to the worst-case estimate. Depending on the direction of the indicator (i.e. whether larger or smaller values are considered more desirable), we subtracted or added multiples m of the standard deviation $SD_{i,l}$ to the nominal value to compute a worst-case estimate.

$$\boldsymbol{y_{i,l,u}} = \begin{cases} \widehat{\boldsymbol{y}}_{i,l}\ \textbf{\textit{for best case}} \\ \widehat{\boldsymbol{y}}_{i,l} - \boldsymbol{m} \times \boldsymbol{SD}_{i,l}\ \textbf{\textit{for worst case, if more is considered better}} \\ \widehat{\boldsymbol{y}}_{i,l} + \boldsymbol{m} \times \boldsymbol{SD}_{i,l}\ \textbf{\textit{for worst case, if less is considered better}} \end{cases}$$

The level of uncertainty is therefore regulated by the factor m, for which we provide examples in the main text. The larger the factor the larger the uncertainty space, and hence the more uncertain events are considered in decision-making.

For each uncertainty scenario the model computes the performance of a hypothetical land-use portfolio for achieving one ecosystem service indicator. The hypothetical land-use portfolio contains various shares, a_l, of each land-use option. We compute the farm-level performance, $Y_{i,u}$, of this portfolio as the sum of the uncertainty adjusted values $y_{i,l,u}$ (i.e. best and worst case estimates) within a given scenario, u, weighted by the area share, a_l, of each land-use in the hypothetical portfolio:

$$Y_{i,u} = \sum_{l} y_{i,l,u} \times a_l$$

As each indicator may be measured in different units, we normalize $Y_{i,u}$ between 0 and 100% to compare performance across different indicators. The best performing uncertainty adjusted indicator within each scenario is set as reference point, i.e. as the 100% target level. Reference points are computed across all uncertainty levels using $m = 3.5$, denoted as $u\ (m = 3.5)$ to guarantee robust results (Gosling et al., 2021). For "more is better" indicators (such as NPV, where high values are more desirable) the highest uncertainty adjusted value within an uncertainty scenario serves as the reference point, $y^*_{i,u\ (m=3.5)} = \max_l \left\{ y_{i,l,u\ (m=3.5)} \right\}$, whereas for "less is better" indicators (such as payback period) it is the lowest indicator value, $y_{i,u\ (m=3.5)^*} = \min_l \left\{ y_{i,l,u\ (m=3.5)} \right\}$.

The normalized distance $D_{i,u}$ to the 100% level is computed for each uncertainty scenario by dividing the difference between the reference point and portfolio performance by the difference between the highest and lowest uncertainty-adjusted values ($\Delta_{i,u\ (m=3.5)}$):

$$\boldsymbol{D_{i,u}} = \begin{cases} \dfrac{y^*_{i,u\ (m=3.5)} - Y_{i,u}}{\Delta_{i,u\ (m=3.5)}} \times \mathbf{100}\ \textbf{\textit{if more is}}\ better \\[2ex] \dfrac{\boldsymbol{Y_{i,u}} - y_{i,u\ (m=3.5)^*}}{\Delta_{i,u\ (m=3.5)}} \times \mathbf{100}\ \textbf{\textit{if less is}}\ better \end{cases}$$

$$\Delta_{i,u\ (m=3.5)} = y^{*}_{i,u\ (m=3.5)} - y_{i,u\ (m=3.5)^{*}}$$

The variable $D_{i,u}$ measures the shortfall between land-use portfolio performance for a given ecosystem service indicator and the reference point (I.e. the best possible or target level). The largest shortfall β, which we describe as underperformance, is defined by the maximum distance $D_{i,u}$ across all uncertainty scenarios:

$$\beta = \max_{i,u}\{D_{i,u}\}$$

The variable β serves as our objective function, which is minimized by solving the allocation problem with the area shares a_l allocated to each land-use type as decision variables.

The optimization problem is formulated as minimize β.

Subject to

$$\beta \geq D_{i,u}\ \forall_i \in I, \forall_u \in U_i$$

$$\sum_l a_l = 1$$

$$a_l \geq 0$$

By minimizing β we seek to obtain the land-use portfolio that minimizes the worst underperformance across all indicators. Our optimization problem can be solved exactly by linear programming.

Table A1
Non-discounted yearly carbon sequestration changes in Mg C per hectare (for the forestry options emissions in year 22 and 45 vary due to the considered product pools after harvesting).

Year of project period	*Pinus patula*	*Pinus elliottii*	*Eucalyptus grandis*	*E. grandis x urophylla*	*Persea americana* Irrigated orchard	*P. americana* Dryland orchard
0	0.00	0.00	0.00	0.00	0.37	0.37
1	0.00	0.00	1.08	1.10	0.37	0.37
2	0.00	0.00	3.99	4.02	0.37	0.37
3	0.03	0.00	5.88	5.93	0.37	0.37
4	1.58	0.30	6.55	6.61	0.37	0.37
5	4.40	2.86	3.52	3.55	0.37	0.37
6	6.47	3.10	7.00	7.06	0.37	0.37
7	6.83	5.93	−3.61	−3.59	0.37	0.37
8	8.10	5.06	6.24	6.29	0.37	0.37
9	6.69	5.17	6.64	6.70	0.37	0.37
10	7.76	6.38	6.60	6.65	0.37	0.37
11	6.59	5.90	6.66	6.72	0.37	0.37
12	−0.41	−0.59	6.73	6.79	0.37	0.37
13	5.49	5.03	6.67	6.71	0.37	0.37
14	5.25	4.84	6.80	6.85	0.37	0.37
15	5.40	4.58	6.53	6.60	0.37	0.37
16	4.36	4.79	6.50	6.52	0.37	0.37
17	4.95	4.80	6.32	6.37	0.37	0.37
18	4.29	5.11	5.97	5.99	0.37	0.37
19	4.10	4.56	6.10	6.15	0.37	0.37
20	3.94	4.86	5.83	5.87	0.37	0.37
21	3.37	4.53	5.38	5.40	0.37	0.37
22	−17.77	−15.81	−31.13	−31.32	0.37	0.37
23	0.00	0.00	0.00	0.00	0.37	0.37
24	0.00	0.00	1.08	1.10	0.37	0.37
25	0.00	0.00	3.99	4.02	0.37	0.37
26	0.03	0.00	5.88	5.93	0.37	0.37
27	1.58	0.30	6.55	6.61	0.37	0.37
28	4.40	2.86	3.52	3.55	0.37	0.37
29	6.47	3.10	7.00	7.06	0.37	0.37
30	6.83	5.93	−3.61	−3.59	0.37	0.37
31	8.10	5.06	6.24	6.29	0.37	0.37
32	6.69	5.17	6.64	6.70	0.37	0.37
33	7.76	6.38	6.60	6.65	0.37	0.37
34	6.59	5.90	6.66	6.72	0.37	0.37
35	−0.41	−0.59	6.73	6.79	0.37	0.37
36	5.49	5.03	6.67	6.71	0.37	0.37
37	5.25	4.84	6.80	6.85	0.37	0.37
38	5.40	4.58	6.53	6.60	0.37	0.37
39	4.36	4.79	6.50	6.52	0.37	0.37
40	4.95	4.80	6.32	6.37	0.37	0.37
41	4.29	5.11	5.97	5.99	0.37	0.37
42	4.10	4.56	6.10	6.15	0.37	0.37
43	3.94	4.86	5.83	5.87	0.37	0.37
44	3.37	4.53	5.38	5.40	0.37	0.37
45	−89.18	−77.20	−113.37	−114.27	−16.65	−16.65

Table A2
Input data for optimization: Cost and benefit relevant indicator values and their standard deviation (based on 5000 Monte-Carlo simulations, NPV = net present value, PP = payback period, CS = carbon sequestration, FU = fertilizer use, number after indicator states used discount rate in percentage).

	Persea americana Cultivar 'Hass' Irrigated orchard		*P. americana* Cultivar 'Hass' Dryland orchard		*Eucalyptus grandis*		*E. grandis* x urophylla		*Pinus elliottii*		*Pinus patula*	
Indicator abbreviation + Discount rate	Average	Standard deviation	Average	Standard deviation	Average	Standard deviation	Average	Standard deviation	Average	Standard deviation	Average	Standard deviation
NPV3 [USD/ha]	52,826.77	12,218.71	28,995.48	9766.98	12,291.04	4004.51	10,186.63	3512.50	2459.99	2104.05	3593.02	2317.79
PP3 [years]	14.02	3.38	17.73	5.48	11.17	6.90	15.63	8.05	29.82	19.21	25.75	13.89
CS0 [Mg C /ha]	0.00	0.00	0.00	0.00	90.44	25.04	90.95	24.92	64.46	16.05	76.84	17.93
CS1 [Mg C /ha]	2.85	0.14	2.85	0.14	87.12	14.57	87.66	14.46	60.47	9.49	73.30	10.30
CS2 [Mg C /ha]	4.30	0.21	4.30	0.21	81.34	8.36	81.89	8.30	55.24	5.79	67.84	5.89
CS3 [Mg C /ha]	4.94	0.25	4.94	0.25	74.72	5.09	75.25	5.10	49.75	4.04	61.77	3.78
FU0 [kg N /ha]	8970.00	448.50	8970.00	448.50	398.00	19.90	398.00	19.90	0.00	0.00	0.00	0.00
FU1 [kg N /ha]	7233.43	361.67	7233.43	361.67	398.00	19.90	398.00	19.90	0.00	0.00	0.00	0.00
FU2 [kg N /ha]	5945.58	297.28	5945.58	297.28	398.00	19.90	398.00	19.90	0.00	0.00	0.00	0.00
FU3 [kg N /ha]	4976.15	248.81	4976.15	248.81	398.00	19.90	398.00	19.90	0.00	0.00	0.00	0.00

Table A3
Discounted sum of carbon sequestration per investment period in Mg C per hectare for selected discount rates (grey shaded cells indicate the basic results with default settings).

Carbon sequestration					
	discount rate	**0.0%**	**1.0%**	**2.0%**	**3.0%**
Pinus patula - 46years project period; no product pools	Sum of discounted carbon sequestration Mg C/ha	11.50	18.22	21.71	23.29
		±22.05	±13.18	±7.80	±4.67
Pinus patula - 46 years project period; product pools lasting for 11 years	Sum of discounted carbon sequestration Mg C/ha	65.23	60.15	55.11	50.34
		±19.56	±13.43	±9.74	±7.60
Pinus patula - 46 years project period; product pools lasting for 28 years	Sum of discounted carbon sequestration Mg C/ha	76.84	73.30	67.84	61.77
		±17.93	±10.30	±5.89	±3.78
Pinus elliottii - 46 years project period; product pools lasting for 28 years	Sum of discounted carbon sequestration Mg C/ha	64.46	60.47	55.24	49.75
		±16.05	±9.49	±5.79	±4.04
Eucalyptus grandis - 46 years project period; product pools lasting for 28 years	Sum of discounted carbon sequestration Mg C/ha	90.44	87.12	81.34	74.72
		±25.04	±14.57	±8.36	±5.09
Eucalyptus grandis x urophylla - 46 years project period; product pools lasting for 28 years	Sum of discounted carbon sequestration Mg C/ha	90.95	87.66	81.89	75.25
		±24.92	±14.46	±8.30	±5.10
Pinus patula - 46 years project period; product pools lasting for >45 years	Sum of discounted carbon sequestration Mg C/ha	140.23	113.80	93.83	78.53
		±8.45	±6.71	±5.79	±5.27
Pinus Patula - 62 years project period; no product pools	Sum of discounted carbon sequestration Mg C/ha	37.62	40.89	40.50	38.54
		±44.08	±25.60	±15.62	±10.13
Pinus patula - 54 years project period; no product pools	Sum of discounted carbon sequestration Mg C/ha	28.27	32.12	32.89	32.12
		±35.97	±22.15	±14.15	±9.46
Persea americana - 46 years project period	Sum of discounted carbon sequestration Mg C/ha	0.00	2.85	4.30	4.94
		±0.00	±0.14	±0.21	±0.25
Persea americana - 54 years project period	Sum of discounted carbon sequestration Mg C/ha	0.00	3.74	5.40	5.95
		±0.00	±0.19	±0.27	±0.30
Persea americana - 62 years project period	Sum of discounted carbon sequestration Mg C/ha	0.00	4.70	6.48	6.89
		±0.00	±0.24	±0.32	±0.34

Table A4
Discounted sum of fertilizer use per investment period in kg N per hectare for selected discount rates (grey shaded cells indicate the basic results with default settings).

Fertilizer use					
	discount rate	0.00%	1.00%	2.00%	3.00%
Pine species - 46 years project period	Sum of discounted fertilizer use kg N/ha	0.00	0.00	0.00	0.00
		±0.00	±0.00	±0.00	±0.00
Eucalyptus species - 46 years project period	Sum of discounted fertilizer use kg N/ha	398.00	398.00	398.00	398.00
		±19.90	±19.90	±19.90	±19.90
Persea americana - 46 years project period	Sum of discounted fertilizer use kg N/ha	8970.00	7233.43	5945.58	4976.15
		±448.50	±361.67	±297.28	±248.81
Persea americana - 54 years project period	Sum of discounted fertilizer use kg N/ha	10530.00	8186.95	6531.53	5338.12
		±526.50	±409.35	±326.58	±266.91
Persea americana - 62 years project period	Sum of discounted fertilizer use kg N/ha	12090.00	9067.51	7031.64	5623.87
		±604.50	±453.38	±351.58	±281.19

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