

Optimizing spatial incentives in markets for conservation services

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Abstract

Market based instruments like auctions or tradable permits have been proposed as flexible and cost-effective instruments for biodiversity conservation on private lands. Trading the service of conservation requires to define a metric which determines to which extent each local conservation measure adds to the conservation objective. A challenge to define such a metric are the different spatial and temporal scales at which ecological processes and economic decisions take place. In this paper, we examine how different spatial metrics perform in a tradable permit market for conservation credits under different economic conditions. Trading of conservation credits is simulated by an agent based model of landusers including different scenarios of dynamic conservation costs. On top of the emerging dynamical landscape, a metapopulation model is used to evaluate conservation success of the tradable permit scheme. We find that successful metrics correlate with species parameters like dispersal distance, but they also depend on the underlying cost surfaces. We conclude that a combined analysis of ecological and socio-economic conditions should be applied when designing market instruments to protect biodiversity.

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1 Introduction

In recent decades, conservation planning has been the prevailing policy to deal with the protection of endangered species and habitats (Margules & Pressey, 2000). Yet, present conservation efforts have so far failed to halt the ongoing decline of species and communities caused by the loss of habitat on private and unprotected lands (MA, 2005). One reason for this is that acquiring and managing conservation areas is costly and this limits the amount of area which can be conserved. Given the pressure from economic growth and the need to mitigate the effects of climate change on ecosystems, it seem unlikely that static reserves alone will suffice to reverse this trend (Sala et al., 2000). Therefore, we urgently need effective strategies for encouraging conservation efforts on private lands to complement existing reserves and achieve a broader global conservation portfolio (Scott et al., 2001; Bengtsson et al., 2003; Newburn et al., 2005).

Market based instruments (MBIs) such as auctions (Latacz-Lohmann & Van der Hamsvoort, 1998; Latacz-Lohmann & Schilizzi, 2005) or biodiversity offset trading (Chomitz, 2004; Drechsler & Watzold, 2007) have been suggested as a means to complement existing reserves by inducing biodiversity protection measures on private lands. Defining conservation as a commodity whose price is subject to competition among the supplying landusers, market instruments promise a cost-effective adaptation of conservation measures to spatially or temporally heterogenous costs as well as more flexibility for policy makers in case of changing conservation priorities.

Like for any conservation scheme, the overall goal of market based instruments is to ensure the persistence of biodiversity in our landscapes (Margules & Pressey, 2000). This goal, however, cannot be traded on a market. What we need is a metric, acting as a surrogate for the goal of persistence. This metric should be well defined and measurable for any local site. A core challenge for finding appropriate metrics for MBIs is that ecological processes may operate on large spatial and temporal scales, while private landowners typically act on much smaller spatial scales and with limited time horizons. In particular, for most real world conservation situations, the ecological value of a typical private property is not independent of neighboring properties. One reason is that for many endangered species not only the absolute loss of habitat area, but also habitat fragmentation is a major cause of population decline. Hence, a market where conservation measures are only valued locally sets the wrong incentives because it does not account for the actual species requirements.

Ecologically more sound metrics including the connectivity of local sites are available and widely used for systematic reserve site selection (Moilanen, 2005; van Teeffelen et al., 2006). These metrics have been developed for assessing and optimizing the total ecological value of a landscape, trying to capture ecological interactions as best as possible. In markets for conservation services, however, a number of landowners is acting independently and with limited knowledge

based on the used metric, striving for maximization of their individual income rather than for maximization of the global welfare. We have to avoid situations where the spatial incentives in the metric create externalities (local decisions create costs or benefits for neighboring landowners) which could lead to inefficient land allocations. Moreover, when metrics get more complicated, we may expect a decreasing probability that landowners will find close to optimal allocations on their land (Hartig & Drechsler, *subm. 2007*). Thus, unlike for reserve site selection, there is a trade-off in defining metrics for MBIs: Ecological accuracy is one goal, but it may be that socio-economic reasoning suggests a compromise towards more practical and robust metrics.

This paper examines which spatial metrics perform most successful and robust in reaching a cost-effective allocation of conservation measures in a market for biodiversity credits. We use the tradable permit market model introduced in (Hartig & Drechsler, *subm. 2007*) to estimate the reactions of landowners towards a given spatial metric. A spatially explicit metapopulation model is placed on top of the emerging landscape structure to evaluate the conservation success in terms of survival probability after a fixed time horizon.

2 Methods

2.1 Overview and purpose

The aim of the model is to optimize the spatial metric in a tradable biodiversity credit market for a single species. The model contains two submodels: An economic submodel which simulates the trading of conservation credits and an ecological submodel on top to assesses the viability of a species in the dynamic landscape which emerges from the trading activity. Driver for the trading and the subsequent change of the landscape configuration is economic change in the region, reflected by heterogeneously changing costs of maintaining a local site in a conserved state. We first describe the state variables of the model, followed by the economic and the ecological submodel and the coupling of the submodels. The coupled model is then used to find the cost-effective metric by comparing the forecasted species persistence across a range of different parameterizations of the metric. Fig. 1 shows a graphical representation of our model approach.

2.2 State variables and scales

The study is conducted on a rectangular 30×30 grid with periodic boundary conditions. The $n = 30 \cdot 30$ grid cells represent both the economic (property) units and the ecological (habitat) units. Grid cells x_i occur in two states only: They can be conserved at a cost c_i and thus provide habitat for the species, or they are used for other economic purposes which result in no costs. The conservation state of a grid cell is labelled with σ_i , $\sigma_i = 1$ being a conserved cell and $\sigma_i = 0$ being a unconserved cell. Conserved grid cells may be either

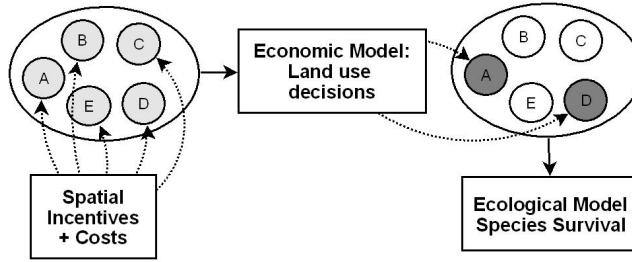


Figure 1: Modelling approach: Driver are spatially heterogeneous, dynamic costs for each site. On base of these costs, land use and conservation measures are allocated by the economic submodel. The resulting dynamic landscape is used as an input for the ecological model which estimates species survival probabilities on this landscape.

populated $p_i = 1$ or unpopulated $p_i = 0$ by the species under consideration. Unconserved grid cells can never be populated. A list of the state variables and parameters of the two submodels is given in Table 1.

SYMBOL	CONNOTATION	RANGE
x_i	Position of the i-th cell on the grid	
σ_i	Conservation state of the i-th cell	$\{0, 1\}$
p_i	Population state of the i-th cell	$\{0, 1\}$
$c_i(t)$	Opportunity costs of $\sigma_i = 1$ at t	$[1 - \Delta \dots 1 + \Delta]$
Δ	Cost heterogeneity	$[0..1]$
ω	Cost correlation	$[0..1]$
m	Connectivity weight	$[0..1]$
l	Connectivity length	$[0..1]$
λ	Conservation target	$[0..1]$
d	Mortality rate	$[0..1]$
r	emigration rate	$[0..\infty]$
r_d	Dispersal rate after destruction	$[0..\infty]$
α^{-1}	Dispersal distance	$[0..\infty]$

Table 1: List of state variables (top), parameters of the economic model (middle) and parameters of the ecological model (bottom)

2.3 Economic Model

The economic model describes the decisions of landowners to establish, maintain, or quit a conservation measure on their land (grid cell). These decisions are driven by dynamic, spatially heterogeneous costs for conserving a grid cell and by the incentives of the tradable permit market, the latter being determined

by the applied metric which decides on the amount of conservation credits to be earned on a particular site. The model is designed as a spatially explicit, agent based partial equilibrium model.

A conserved grid cell of unit size produces a certain amount of conservation credits ξ depending on the number of conserved grid cells in its neighborhood. We use the following metric to determine ξ :

$$\xi = (1 - m) + m \cdot \zeta(l) . \quad (1)$$

The first term $1 - m$ is independent of the connectivity and may be seen as an base reward for the conserved area. The parameter m is a weighting factor determining the importance of connectivity compared to area. The second term $m \cdot \zeta(l)$ includes the connectivity of the site, measured by the proportion of conserved sites within a circle of radius l .

$$\zeta_i(l) = \left(\sum_{|x_i - x_j| < l} \sigma_j \right) \cdot \left(\sum_{|x_i - x_j| < l} 1 \right)^{-1} \quad (2)$$

The total amount of credits in the market is given by the sum of the ξ_i over all conserved grid cells.

$$U = \sum_{i=1}^n \sigma_i \xi_i \quad (3)$$

The conservation of a site results not only in conservation credits, but also in costs which differ among grid cells. We use three different algorithms to generate a surface of random dynamic costs $c_i(t)$. The first option (Algorithm 1) are spatially and temporally uncorrelated random costs drawn from a uniform distribution of width $2 \cdot \Delta$ at each time step. Algorithm 2 creates spatially uncorrelated, but temporally correlated costs by applying on each grid cell a random walk of maximum step length Δ together with a small rebounding effect towards 1, controlled by ω . Algorithm 3 uses a random walk of maximum step length Δ combined with a correction term of strength ω towards the average costs in the neighborhood, which creates spatio-temporally correlated costs. All algorithms result in average costs of 1, but they differ in the spatial and temporal distribution of costs (see also Fig. 2 and Fig. 3).

Algorithm 1 Random costs

- 1: **for all** cells **do**
 - 2: $c_i(t) = \text{random}[1 - \Delta \cdots 1 + \Delta]$
 - 3: **end for**
-

Algorithm 2 Random walk

- 1: **for all cells do**
 - 2: $c_i(t) = c_i(t-1) + \Delta \cdot \text{random}[-1 \cdots 1] + \omega \cdot \text{sign}(1 - c_i(t-1)) \cdot \sqrt{|1 - c_i(t-1)|}$
 - 3: **end for**
-

Algorithm 3 Correlated random walk

- 1: Calculate average global costs
 - 2: **for all cells do**
 - 3: $\bar{c}_i =$ average costs in the 8-cell neighborhood
 - 4: $c_i(t) = c_i(t-1) + \Delta \cdot \text{random}[-1 \cdots 1] + \omega \cdot \bar{c}_i$
 - 5: Normalize with average global costs
 - 6: **end for**
-

To simulate the trading and the formation of a market price, we introduce a market price P for credits. Each landowner decides on the base of his costs and the conservation credits to be earned whether to conserve his land or not. The model has two options for determining the equilibrium price of the market: Either the price is adjusted until a certain target level for the total amount of produced conservation credits U (eq. 3) is met, or the price is adjusted until a certain level of aggregated costs for the conservation is reached. By aggregated costs, we mean the sum of the costs of all conserved sites,

$$C = \sum_{i=1}^n \sigma_i c_i . \quad (4)$$

The first option, fixing the target, reflects most accurately the functioning of a tradable permit market, however, because our costs are globally in a steady state and the simulation runs on a fairly large number of grid cells, fixing the budget results in conservation credits U being practically constant over time, too.¹ We therefore chose the latter option of fixing the budget for the analysis because it allows an easier comparison between different metrics. A detailed analysis of the economic model can be found in (Hartig & Drechsler, subm. 2007). Algorithm 4 shows the scheduling of the model within one time step.

¹To ensure that the random walks are in a steady state, we let the simulation run for 10000 time steps until the populations are initialized.

Algorithm 4 Scheduling Economic Model

Change costs
repeat
 Adjust market price P
 for all cells **do**
 if $P \cdot \xi_i(l) > c_i(t)$ **then**
 $x_i = 1$ (conserved)
 else
 $x_i = 0$ (not conserved)
 end if
 end for
 Calculate ecological value and costs
until Budget constraint is met

2.4 Ecological Model

To evaluate conservation success in the emerging dynamic landscapes, we use a stochastic metapopulation model (see Hanski, 1998, 1999, for an overview about metapopulations in ecology). Each conserved grid cell is treated as a habitat patch, meaning that each grid cell may hold a local population of the species. Local populations produce emigrants which may disperse and establish a new local population on an unoccupied cell. At the same time, local populations are subject to local extinction which may be caused e.g. by demographic or environmental stochasticity. The population as a whole can persist on the landscape if the average recolonization rate is higher than the average local extinction risk, yet, stochastic fluctuations of the number of populated patches may eventually cause an extinction of the whole population. The better the connectivity among patches, and the more patches in the network, the lower is the probability of such an extinction.

Local extinctions are modelled by a constant chance d of each patch to go extinct per time step. The amount of immigrants arriving at an unpopulated patch from a populated patch is given by the following dispersal kernel

$$p_{ij} = r \cdot \frac{1}{\sum_i \sigma_i - 1} \cdot e^{-\alpha \cdot d_{ij}} \quad (5)$$

where r is the emigration rate, the following term $\frac{1}{\sum_i \sigma_i - 1}$ distributes the dispersal among the available habitat patches, and the exponential term describes losses during dispersal. If a patch has been destroyed at the current time step, we set the dispersal rate to r_d , assuming that a proportion of r_d of the population will be able to disperse before destruction. The sum of all arriving immigrants according to eq. 5 (truncated to 1) is taken as the probability that this patch is colonized at the current time step. The scheduling of the metapopulation model within one time step is sketched in algorithm 5. Table 1 gives an overview of the model parameters.

Algorithm 5 Scheduling Metapopulation Model

```
1: for all Populated cells do
2:   Local extinction
3: end for
4: for all Populated cells do
5:   if Patch destroyed then
6:     Disperse with emigration rate  $r_d$ 
7:   else
8:     Disperse with emigration rate  $r$ 
9:   end if
10: end for
11: for all Unpopulated cells do
12:   Check if immigration successful
13: end for
```

2.5 Parametrization and analysis of the model

Since species have different spatial habitat requirements depending on their dispersal abilities, we expect that an efficient spatial metric should reflect this need through its parameter setting for connectivity weight m and connectivity length l . Additionally, there may be an impact of the economic conditions. Therefore, we varied both the connectivity weight m and the connectivity length l of the metric eq. 1 for three different cost scenarios and for three different species types.

The three cost scenarios were generated by random costs (Alg. 1) at $\Delta = 0.2$, the random walk (Alg. 2) at $\Delta = 5 \cdot 10^{-5}$ and $\omega = 0.0065$ and the correlated random walk (Alg. 3) at $\Delta = 0.015$ and $\omega = 0.006$. Table 2 displays a summary of the three scenarios. Remember that Alg. 3 creates spatio-temporally correlated costs, Alg. 2 creates temporally correlated costs and Alg. 1 creates totally uncorrelated costs. The latter is displayed in Fig. 2, which shows snapshots of typical spatial cost distributions generated by the two random walk algorithms, and by Fig. 3 which shows a time series of the costs created by the three Algorithms.

COST SCENARIO	PARAMETERS	CHARACTERISTICS
1 - RANDOM	$\Delta = 0.2$	not correlated
2 - RANDOM WALK	$\Delta = 5 \cdot 10^{-5}, \omega = 0.0065$	time correlated
3 - CORRELATED WALK	$\Delta = 0.015, \omega = 0.006$	space and time correlated

Table 2: Overview of the cost scenarios created by the three algorithms.

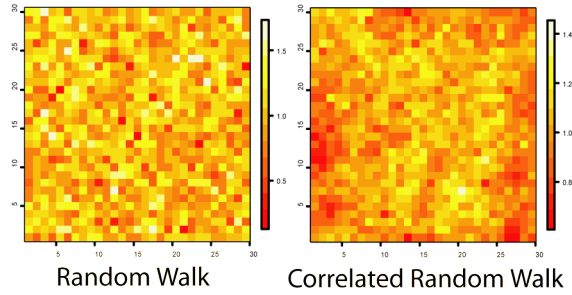


Figure 2: Spatial cost distributions generated by the random walk algorithms (Alg. 2 and 3). The two figures shows the 30×30 grid cells with high cost cells in light and low cost cells in dark colors. The left figure was created by the random walk (algorithm 2) at $\Delta = 5 \cdot 10^{-5}$, $\omega = 0.0065$, to the right the correlated random walk (algorithm 3) at $\Delta = 0.015$, $\omega = 0.006$. Note that low and high cost areas are clustered for the correlated random walk.

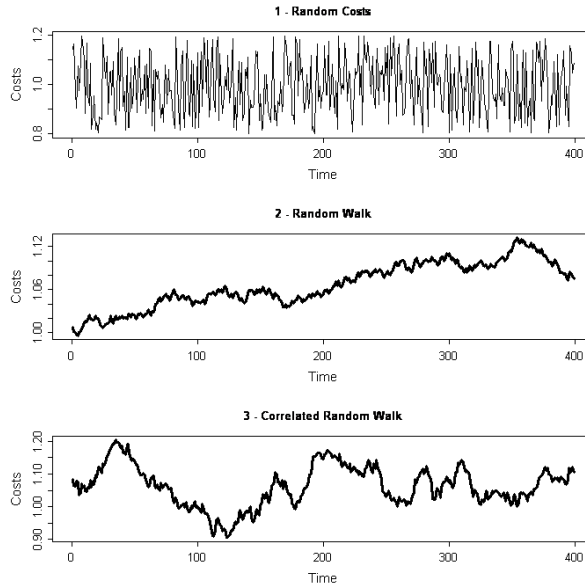


Figure 3: Time series of the costs of a grid cell over time. Algorithm 1 which changes costs randomly at each time step creates a fluctuating time series. The two random walk algorithms lead to a time-correlated series.

For the species, we consider three functional types, one with a short dispersal ability, one with an intermediate dispersal ability and one with no dispersal limitation. The parametrization for the three species is displayed in Table 3. To assess the conservation success, i.e. the extinction risk of the species, we ran the simulation a sufficient number of times and calculated the probability

of extinction after 1000 time steps. We checked that the population is in the steady state after initialization and thus the measurement is not affected by the initialization (see Grimm & Wissel (2004) for a discussion about measuring mean time to extinction from counting extinction events). A typical histogram of extinction events over time is shown in Fig. 4.

SPECIES TYPE	\mathbf{d}	\mathbf{r}	\mathbf{r}_d	α^{-1}
I - SHORT DISPERSAL	0.29	3	1	5
II - INTERMEDIATE DISPERSAL	0.51	3	1	25
III - GLOBAL DISPERSAL	0.66	3	1	1000

Table 3: Parameter values for the three species types considered.

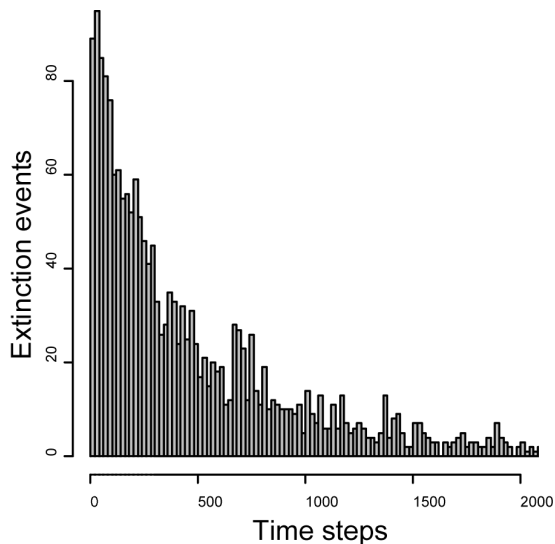


Figure 4: Histogram of extinction events, giving an approximation for survival probability over time. The plot is created by 2000 runs of species II under correlated costs (algorithm 3) at $m = 0.5, l = 1.5$. Populations in a metastable steady state are subject to a constant extinction risk per time step, which gives rise to the exponential decay of survival probability displayed in the figure. The exponential decay starts near the first time steps, suggesting that the population is practically at equilibrium after initialization.

The aggregated costs (eq. 4) for the conservation scheme were fixed to 0.03 times the number of grid cells n for scenarios with costs surfaces generated by the random walk algorithms (Alg. 2 and 3) and to 0.05 times the number of grid cells n for scenarios created with the random algorithm (Alg. 1). Exceptions

are the combination Alg. 3 with species 3 where aggregated costs were set to 0.1 times n and Alg. 1 with species 3 where aggregated costs were set to 0.18 times n . The adjustment to different budgets was done to create similar survival probabilities across the 9 scenarios for an easier comparison of the results.

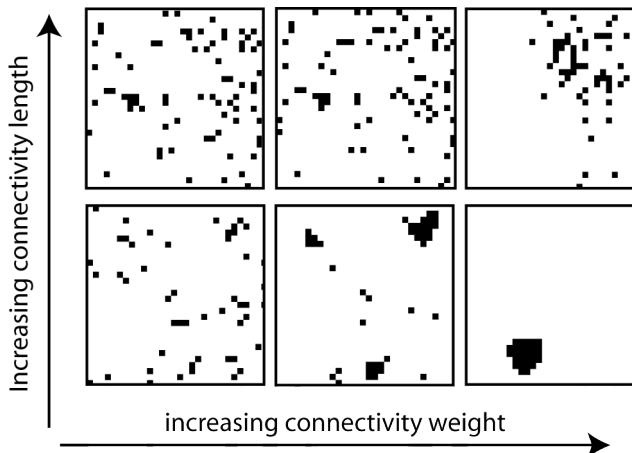


Figure 5: Effect of the connectivity weight m and the connectivity length l . The three pictures show typical landscape structures emerging from trading with costs being sample by algorithm 2 at $\Delta = 5 \cdot 10^{-5}$, $\omega = 0.0065$. Conserved sites are colored black, other sites are colored white. The top row is created with a long connectivity length ($l = 10$), the bottom row with a short connectivity length ($l = 1.5$). The pictures in the left column are taken at $m = 0$, which means that no weight is put on connectivity. Consequently, the landscape structure is totally dominated by the sites of lowest costs. Increasing connectivity weight ($m = 0.5$ middle, $m = 1$ right) results in an increasing clustering of conservation measures, but in a smaller total area. At a connectivity weight of $m = 1$, meaning that all weight is put on connectivity, $l = 1.5$ results in a very dense cluster, while the larger connectivity length $l = 10$ results in a more spread out configuration.

3 Results

3.1 Emerging Landscapes

For all cost scenarios and all connectivity lengths, an increase in connectivity weight results in more aggregated landscape structures. The density of the clustering is controlled by the connectivity length l , which determines how close patches have to be to count as connected and therefore gain more conservation credits. Smaller connectivity lengths ($l \sim 1.5$ which corresponds to the direct 8-cell neighborhood) result in very dense clusters at full connectivity weight, while larger connectivity lengths lead to more loose agglomerations of conservation measures. Due to the spatial cost heterogeneity, there is a trade off between clustering and area: At a fixed budget, a higher connectivity weight results in

lower total area, but with higher clustering. Typical landscapes are displayed in Fig. 5.

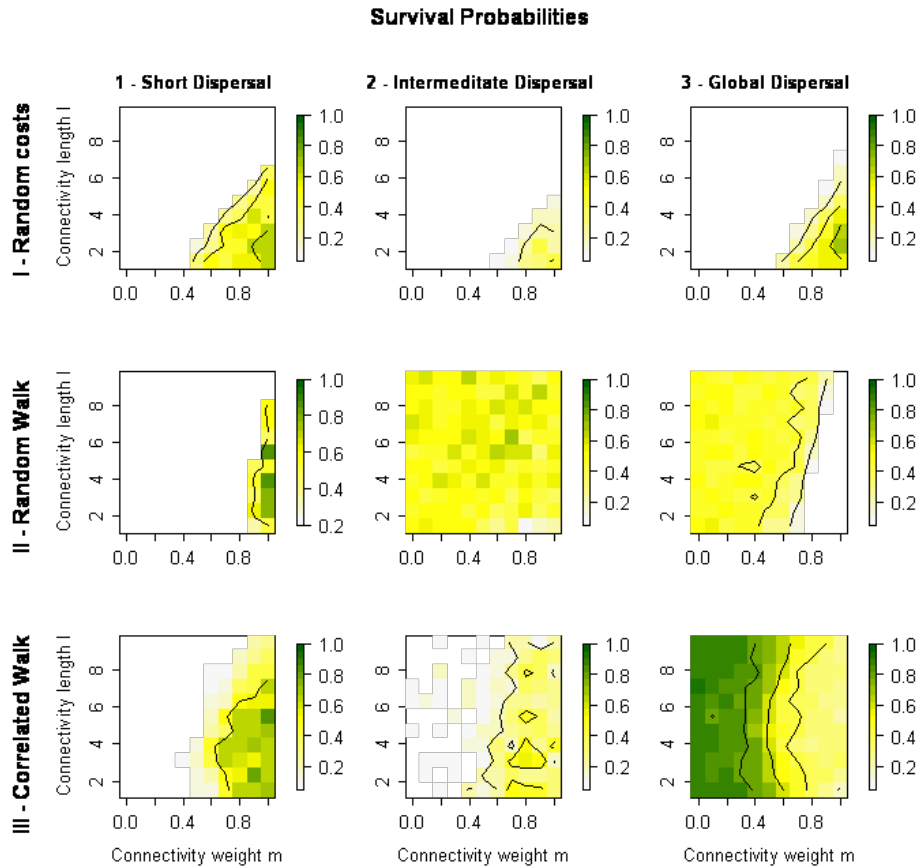


Figure 6: Survival probability as a function of connectivity weight (x-axis) and connectivity length (y-axis) for the three species types (columns 1-3) and for three cost scenarios (rows 1-3). Dark values represent high survival probabilities.

3.2 Optimal Incentive

To find the most effective spatial metric, we varied connectivity weight between 0 and 1 and connectivity length between 1.5 and 9.5 in 11 linear steps each. The resulting survival probabilities after 1000 years for the three cost scenarios and the three species types are shown in Fig. 6. The results show that species I (short disperser) generally requires a very high connectivity weight and short to medium connectivity lengths, species II (intermediate disperser) requires different settings depending on the cost scenario, and species III (global disperser)

benefits from a low connectivity weight and is relatively insensitive towards the connectivity length. An exception are the scenarios generated with random costs (Alg. 1), which require very high connectivity weight and short connectivity lengths for all species. While it is certainly not surprising that the short and the global disperser are placed on opposite sides of the trade off between clustering and area, it is somewhat surprising that the cost scenarios, in particular the random costs, lead to such a strong difference in the cost-effective parametrization of the metric. We will explore the reason for this in the next subsection.

3.3 Cost Scenarios and Landscape Measures

From the observed influence of the cost scenario on the effectiveness of the applied metric, it is obvious that the emerging landscapes differ among the different cost scenarios. To analyze this difference, we plotted connectivity and also turnover (fraction of patches reallocated per time step) as a function of the metric parameters m and l for the three considered cost scenarios (Fig. 7).

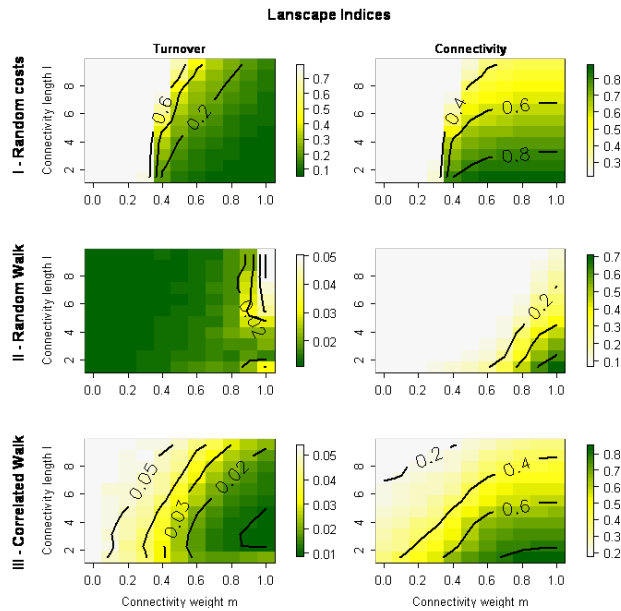


Figure 7: Connectivity and turnover for the three cost scenarios as a function connectivity weight m and the connectivity length l for three different cost scenarios (rows 1-3). Connectivity of a conserved patch is measured as percentage of conserved cells in the direct 8-cell (Moore) neighborhood. Turnover, the fraction of conserved cells being destroyed at each time step, serves as an estimate for the intensity of landscape dynamics. Dark values represent low turnover and high connectivity, respectively.

We find that turnover and connectivity differ between the different cost scenarios not only in magnitude, but also in shape and sometimes even in sign of the relationship. For example, for the case of the correlated random walk (Alg. 3), turnover decreases with increasing connectivity weight m , while the scenario with a spatially uncorrelated random walk (2) displays an increase of turnover in the same situation. The latter explains the difference between the two cost scenarios for the intermediate disperser, where the scenario with Alg. 2 was largely insensitive to the connectivity weight, while the scenario with Alg. 3 showed a preference for a strong connectivity weight. The observed strong difference in efficient parameter settings of the metric between the random costs scenario and the random walk scenarios originates probably mainly from the magnitude of turnover. The random cost surface creates significantly higher turnover rates than the other two scenarios, in particular outside the region of high connectivity weight and small connectivity length. The reason for this is that the random cost scenario creates temporally uncorrelated cost, while cost are temporally correlated for the two random walk scenarios (Alg 2, 3) as has been shown in Fig. 3.

4 Discussion

Markets for environmental services are widely discussed as a flexible and cost-effective policy for conservation on private lands. We have proposed a coupled ecological-economic model to optimize the spatial metric which determines the conservational value of a local conservation measure. For the considered species, clustering is generally beneficial, but so is a larger area because it also decreases the extinction risk for the species. Therefore, spatially heterogeneous opportunity costs for conservation create a trade-off between clustering and the larger conservation area which can be achieved by a more spread landscape configuration.

Generally, we find that short dispersing species do best with a strong connectivity weight and a medium connectivity length, while global dispersers do better with a low connectivity weight which results in more total area conserved. Besides this not particularly surprising rule, we find that the characteristics of the underlying cost surface may have an additional and potentially large influence on the exact parameter range which performed well for a particular species. The reason is that the dynamic landscapes which emerge from the market differ among the different cost scenarios. A particularly important factor seems to be the rate of turnover, i.e. the amount of conservation measures which is shifted in position per time step. Such a shift is not punished in the applied metric, but it is deleterious to the species because it effectively increases the local extinction rate. The latter explains the large difference between the effective metrics for the scenarios with random costs and the rest of the scenarios: As we showed in Fig 7, random costs lead to very high turnover rates at low connectivity weight. Therefore, metrics with low connectivity weight are generally disfavored, re-

ardless of the species characteristic.

We believe there are two important points to be learned from these results. The first point is a practical one: Any real conservation credit market will have to address the problem of controlling the emerging landscape dynamics in a more explicit way. Neglecting landscape dynamics may lead to severe problems for the ecological effectiveness. For example, if conserved sites are maintained shorter than the time which is typically required for their colonization, they are typically not contributing to the species population dynamics. Yet, a purely static metric would value them in the same way as a permanently conserved site. One possibility to avoid such effects would be to introduce a minimum duration of conservation measures, however, long minimum durations may constrain the trading on the market and reduce efficiency, while short minimum durations may lead to a declining ecological effectiveness. Another possibility would be to introduce the duration of the conservation measure explicitly in the metric determining the market value of a conserved site. Optimal control of the dynamics of such a market will, however, remain a more challenging problem than controlling the spatial allocation; while the spatial allocation can be perfectly known at each time step, the amount of turnover in the future is unknown and may only be guessed. If population dynamics are slow compared to the economic dynamics, it will be difficult to find rules which ensure a close to optimal temporal allocation of turnover.

The second point is more fundamental: Market instruments for conservation will always have to work with surrogate measures, acting as representation of what we really want to achieve. For example, we used area and connectivity as a surrogate for species persistence in this study. Using surrogates is unavoidable for any practical conservation scheme. Still, we have to be aware at any time that surrogates, may they be naive or very sophisticated, are only approximations of the process we want to preserve. Approximations generally work well on the domain they have been designed for, but they may perform poorly if applied on another domain. Thus, although it is probably sensible to add turnover to our metric to refine the assessment of conservational value, such a refined metric will still remain an approximation. We would expect such a more detailed metric to be more robust on the considered cost scenarios, but we should have in mind that it may still not be robust for all scenarios.

Concluding, we believe that conservation markets offer a cost-effective policy to maintain and improve land use and habitat structure for biodiversity on the large unprotected areas outside existing reserves. Our simulations show that it is possible to account for complicated spatial ecological interactions with relatively simple spatial metrics. Given that most existing schemes worldwide do not explicitly account for such spatial processes, it seems promising to examine the potential efficiency gains which could be realized by applying spatially explicit metrics for market based conservation. However, because these metrics are only a surrogate for the real species requirements, they are not universal.

A particular metric may work well in a particular socio-economic setting, but may perform poorly in a different one. As explicitly accounting for all ecological processes in the trading rules seems counterproductive for creating a working market as well as unfeasible for the planner, metrics for market based instruments will most likely always contain approximations. The message of this paper is that these approximations are not context-free, but particular to the socio-economic setting they are applied to. Thus, a thorough examination both of the ecological as well as the economic and social background is required for deciding on spatial metrics for market based instruments.

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